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Capturing complex processes of human performance

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2015

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):
den Hartigh, J. R. (2015). *Capturing complex processes of human performance: Insights from the domain of sports*. University of Groningen.

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Capturing Complex Processes of Human Performance

Insights from the Domain of Sports

Ruud den Hartigh

The research presented in this dissertation was funded by a PhD grant from the University of Montpellier, awarded by the École Doctorale 463 (Sciences du Mouvement Humain), and was financially supported by the Heymans Institute of the University of Groningen.

Cover design: Sanne van Gent

Printed by: Ipskamp drukkers

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ISBN: 978-90-367-7722-3 (paper version)

ISBN: 978-90-367-7721-6 (electronic version)

Capturing Complex Processes of Human Performance

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Proefschrift

ter verkrijging van de graad van doctor aan de
Rijksuniversiteit Groningen
op gezag van de
rector magnificus prof. dr. E. Sterken
en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op

donderdag 16 april 2015 om 16.15 uur

door

Jan Rudolf den Hartigh

geboren op 16 augustus 1984
te Korendijk

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Collège Doctoral du Languedoc-Roussillon

THÈSE

Pour obtenir le grade de

Docteur

Délivré par l'**Université de Montpellier**

Préparée au sein de l'école doctorale 463
Sciences du Mouvement Humain
Et de l'unité de recherche EA 4556
Dynamique des Capacités Humaines et des Conduites de Santé

Présentée par **Jan Rudolf DEN HARTIGH**

CAPTURING COMPLEX PROCESSES OF HUMAN PERFORMANCE : INSIGHTS FROM THE DOMAIN OF SPORTS

La soutenance publique aura lieu le 16 Avril 2015

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Chapter 1: Introduction

This chapter is an adapted version of (to appear):

Den Hartigh, R. J. R., Cox, R. F. A., & Van Geert, P. L. C. (2015). What model should we use to explain the complexity of cognition? The answer is not complicated. In L. Magnani, & T. Bertolotti (Eds.), *Springer Handbook of Model-Based Science.*

The processes involved in human performance seem inherently *complex* and *dynamic*. For example, in order to “read the game”, a soccer player must integrate all the information from the ongoing movements and positions of team members, the opponents, the relative positions between them, where the ball is located, etc. Furthermore, an individual’s motor performance, which is particularly crucial in sports, depends on various simultaneous processes at different levels of the motor system: Cells, muscles, limbs, the brain, and so forth. In addition, individuals and teams do not perform in a void, but in achievement contexts, in which they strive for their goals, and their psychological states and performance may fluctuate as a function of many personal and environmental factors. For example, an athlete may enter a positive or negative spiral when perceiving that he or she is progressing or regressing in relation to the preferred goal or outcome (e.g., the victory). This perception of progress and regress, and the positive and negative psychological and behavioral (performance) changes accompanying this perception, are called positive and negative *psychological momentum* (PM; e.g., Gernigon, Briki, & Eykens, 2010). Positive and negative PM can emerge from one’s (or the opponent’s) mistakes, referee decisions, crowd behaviors, one’s psychological and physical state at a certain moment, and the interactions between these factors (Taylor & Demick, 1994). In addition, switching from performance on a relatively short time frame to a long-term process, individuals develop their abilities over multiple years, and hence over many practice or competition occasions. Ultimately, very few individuals develop world-class performance (e.g., winning Olympic medals), and their excellent abilities develop out of a combination of a variety of personal and environmental factors in interaction (e.g., motivation, coaching, family support, practice; Simonton, 1999).

The current dissertation aims to capture complex dynamic performance-related processes, including the topics illustrated above. This means that we examine complexity at different levels and time scales (from motor processes during one task, up to ability development during a career; see Table 1).

Table 1. Overview of the dissertation. Each chapter has a different focus on complex processes and time scales.

Chapter	Focus (complex processes)	Time scale(s)
2	Level of complexity of cognitive skills, measured while watching soccer game plays	Single game plays (video clips)
3	Complexity of motor organization, measured during ergometer rowing	Single rowing ergometer session consisting of 550 rowing strokes
4	Dynamics of psychological momentum in teams, measured during ergometer races	Single ergometer race
5	Connection between short and long-term psychological momentum, measured during and across ergometer races	Single ergometer race, as well as a sequence of ergometer races
6	Development of excellence out of complexity, modeled over the course of a career	Life span of ability development

The studies have been conducted in a sports context, in which ongoing psychological and performance processes take place. These processes (e.g., PM, talent development) are, however, also relevant to other achievement contexts such as education and business (Day, Gordon, & Fink, 2012), in which individuals or teams are typically considered as goal-oriented, performance-driven agents (e.g., Katz, 2001). That said, the sports context provides particularly well-defined performance criteria (e.g., winning or losing), the actions needed to meet those criteria are clear (e.g., scoring goals in soccer), and performers can often be studied on a relatively small surface (e.g., a soccer field) within a relatively short time frame (e.g., a match).

1.1 Why Would Performance Processes Be Complex?

The word *complex* is mentioned several times in this chapter. Importantly, complexity is not just reflected in the number of components that are involved in psychological and performance processes (e.g., the number and kinds of cells or muscles that are active during performance, the number of personal and environmental variables that shape the development of excellence). Instead, a complex phenomenon or system is characterized by emergence and adaptation. More specifically, with regard to human performance this is the emergence and adaptation of psychological and performance states from the ongoing *interaction* between various intrapersonal (psychological and physical) and situational components (e.g., Kello et al., 2010; Kelso, 1995; Van Geert & Fischer, 2009). This conceptualization is different from the notion of *complicatedness*. In a complicated system many components are involved, which can be studied in isolation, and the resulting psychological and performance states can be understood when knowing the contributions of the individual components (Ottino, 2004). In other words, a resulting state, such as world-class sport performance, can be understood from the addition of a number of causal components (e.g., motivation, physical skills, personality), that can therefore be studied in isolation in order to understand why some individuals develop world-class performance. The complexity perspective, however, assumes that the underlying mechanism of a certain state is multi-causal and dynamic, making it virtually impossible to reduce the explanation to one or a few directly-identifiable components.

However, researchers in the domain of social sciences have primarily attempted to untangle the *complicatedness* underlying human behavior. That is, by isolating one or a few independent variables researchers aimed to find an explanation for the occurrence of a psychological or performance state within a sample of participants (see also Van Geert, 2009a for a related discussion on static versus dynamic models of explanation). This entails that not the process itself (e.g., talent *development*) is studied, but how the results of those processes (e.g., world-class performance) are distributed over the population, and relate to other measurable components within the population (e.g., physical characteristics, motivation). The principal question that follows from this aim is whether the variance in some potential (performance) predictor *x* explains a significant portion of variance in performance outcome *y* (Atkinson & Nevill, 2001).

To give an illustration, with regard to talent or excellence development, typical questions would be what the contributions are of, for example, genes, amount of practice, environmental support, or cognitive commitment to become an excellent performer. Studies focusing on such questions have provided important insights into the kinds of factors contributing to excellent performance. For example, Van Yperen (2009) assessed—amongst other things—the goal commitment (independent variable) of youth AJAX players of the same cohort with a questionnaire. Fifteen years later he determined the career success (dependent variable) of the players (i.e., who had been playing in the Premier league in The Netherlands or another European country for at least 10 years, and who eventually did not end up playing in a professional league). When analyzing the results, Van Yperen (2009) controlled for potential confounds such as the soccer level of the players at the time of data collection (i.e., 15 years earlier). He found that players having a successful career also had a higher goal commitment at the time they were assessed in the youth academy, thereby marking goal commitment as a potential causal component of ultimate excellent performance, and demonstrating that psychological variables may play a pivotal role in talent development. More specifically, Van Yperen (2009) found that goal commitment explained 14% of the variance in soccer players' career success.

Continuing with the example of the study of Van Yperen (2009), while 14% explained variance is a large portion according to the guidelines in social sciences (Cohen, 1988), 86% was not accounted for by the variable goal commitment. It is obvious that various other factors play a role, yet it remains highly probable that we will never come close to explaining 100% of the variance, even if all substantial factors are included. Although the prevailing interpretation for this would be that measurements always involve random error variance (Van Geert & Van Dijk, 2002), an alternative perspective could be that the underlying components of human performance are in an *ongoing interaction*, which provides the principal explanation for the development of career success. For example, support from parents and friends, recent successes and investments of the coach may influence the goal commitment of a player, which in turn positively influences the supporting environment again, and so on (cf. Phillips, Davids, Renshaw, & Portus, 2010). Note that the dynamic interactions we refer to here are different from the interaction effects studied in the social sciences. These are generally limited to 2 or 3 interacting factors, often with a limited number of levels. Hence, the conventional method is to refine models using an additive strategy (adding factors and interaction effects to causal models). Using this method, a newly added variable or interaction term will often lead to only a minor gain in explained variance of the resultant psychological or performance state (Van Geert, 2009a). Therefore, this dissertation explores new models (rather than new potential determinants) to capture the complex processes of human performance.

Note that this dissertation is not intended to falsify or criticize the approach that is based on studying the (isolated) components that contribute to human performance (i.e. complicated models). This approach does provide important information, particularly if the research aim is to explain the distribution of human performance in the population, based on the distribution of specific causal underlying components. However, the current dissertation aims to capture the complex *processes* underlying human performance states, that is, how psychological and performance states emerge out of the *ongoing interaction* between various intrapersonal (psychological and physiological) and situational components. In order to do so, an important step is to find and apply the tools to measure the emergence and adaptation of complex psychological and performance patterns.

Although the complexity approach is not mainstream in the domain of social sciences, it has rapidly grown across different scientific domains (e.g., Gleick, 2008; Kauffman, 1995; Strogatz, 2003). Furthermore, its merits are increasingly recognized in the study of social dynamics (Castellano, Fortunato, & Loreto, 2009), developmental psychology (e.g., Van Geert, 2000), and sport sciences (e.g., Davids et al., 2014; Gernigon et al., 2010). The methods we apply here are thus inspired by applications and propositions from several scientific domains, including nonlinear dynamical systems in learning and development (e.g., Newell, Liu, & Mayer-Kress, 2001; Thelen & Smith, 1994; Van Geert, 1991; 1994; 2000), dynamical social psychology (Nowak & Vallacher, 1998; Vallacher, Read, & Nowak, 2002), synergetics (e.g., Haken, 1977; 1983; Haken, Kelso, & Bunz, 1985), self-organized critical dynamical systems in physics, biology, and cognitive psychology (e.g., Bak, Tang, & Wiesenfeld, 1987; Glass, 2001; Van Orden, Holden, & Turvey, 2003), network science (Newman, Barabási, & Watts, 2006), and mathematical modeling (e.g., Van Geert, 1991; Van der Maas et al., 2006).

1.2 How Can We Capture Complex Processes of Human Performance?

In order to provide insights into the complex processes involved in human performance, the research focus should be on obtaining an understanding of higher-order psychological and performance patterns, and the underlying system of dynamically interacting components (Nowak & Vallacher, 1998). Throughout this dissertation we propose different methods and techniques to capture complexity in various performance-related processes. Chapter 2 starts with an approach based on Skill Theory (Fischer, 1980). Skill theory lends itself particularly well to extract a measure of *complexity in cognitive skills*, which corresponds to a higher order measure reflecting the way individuals (continuously) structure the components in the world they perceive or interact with (Fischer & Bidell, 2006). Using Skill Theory, complexity can be extracted from actions and verbalizations while individuals are exposed to, or interact with, task material (Van Der Steen, Steenbeek, & Van Geert, 2012). Chapter 3 demonstrates how we can extract a measure of complexity that is assumed to reflect the *underlying complex dynamic organization* from which actual performance emerges. In this chapter complexity thus refers to the underlying system that generates human performance, which can be captured with nonlinear time series techniques applied to real-time performance data.

For the Chapters 4 and 5 we identified some important (collective) psychological and behavioral variables, whose changes would provide insights into the dynamics of a specific complex, performance related phenomenon: Psychological momentum (PM). We specifically study how these collective variables change under the influence of experimentally applied perturbations (i.e., progressing or regressing in relation to one's goal in competitive sport situations). In Chapter 6, we use mathematical modeling techniques in order to capture performance patterns on the long term, during the development of excellence. Here, the complexity is reflected in the ongoing interactions between the components, and the fact that the developmental trajectories towards excellent performance are a function of these interacting (changing) components.

The methods we employ in the different studies should of course stem from solid theoretical considerations that warrant their applications to the study of (complex) human performance processes. The methods and their theoretical underpinnings for each subsequent chapter are therefore elaborated on below.

1.3 Capturing Complexity of Athletes' Cognitive Skills (Chapter 2)

Expert athletes have been found to outperform non-experts in terms of their perceptual-cognitive skills (Mann, Williams, Ward, & Janelle, 2007). For instance, experts are able to anticipate events faster and more accurately (e.g., predicting the direction of a cross), and make better decisions than non-expert players (e.g., deciding where to move to receive the ball from a team member; for a demonstration of such skills in a famous expert—Christiano Ronaldo—, see https://www.youtube.com/watch?v=vSL-gPMPVXI). These skills would emerge from the continuous information pick-up of the athletes, which makes an athlete able to "read the game" (Bjurwill, 1993; Williams, 2000). Examples of relevant information in soccer, for instance, are the ball, opponents, team members, and their movements or changing positions. In addition, experts would pay attention to postural and bodily orientation information, mostly the shooting side of the player including the hip, leg, and foot (Williams, 2000). A soccer player thus constructs his (dynamic) representation of the actions taking place on the soccer field, which is based on the integration of multiple elements in continuous interaction (e.g., the players, opponents, ball, etc.). Capturing the complexity (i.e., the integration of the interacting components) of these representations has remained a challenge for researchers (e.g., McPherson, 2000; Roca, Ford, McRobert, & Williams, 2011).

In the domain of developmental psychology, Fischer (1980) has developed a cognitive-developmental theory, proposing that development (or improvement) of cognitive skills can be expressed in terms of increasing complexity (Fischer, 1980; Fischer & Bidell, 2006). Related to this, Fischer proposed a complexity scale along which cognitive skills could be classified according to the way task- or object-related components are integrated to construct a (dynamic) representation. The scale ranges from a representation of one single observable characteristic of the task or object under study—single sensorimotor level—onto a representation of the relations between characteristics that constitute high (complexity) level properties of the task or object—abstraction level. Although this theory has never been applied to the achievement domain of sports, its applicability has been proven in other domains, science education in particular. For instance, in a recent study conducted by my favorite colleague, Van Der Steen (2014), the complexity of children's representations of gravity and air pressure was examined. The complexity level of a child with regard to gravity, for instance, was reflected in the verbalizations of the child while working on a gravity task. If the researcher would release a ball, and would ask the child to explain what happened, the child could answer at different levels. An answer at the sensorimotor level would be “The ball falls down”, which is simple and directly observable. If the child would have given the (unlikely) answer that “gravity caused the ball to fall down when you released it”, it would reflect an abstract level, because the explanation is more than a simple observation of what happens and includes a general understanding of the law that explains the ball falling down from the moment it is released.

Because of (a) the challenge to capture the complexity of (dynamic) representations that athletes such as soccer players construct during game plays, (b) the potential of Skill Theory to measure the complexity of representations that are constructed, and (c) the previous successful applications of Skill Theory in educational contexts, Chapter 2 attempts to measure the complexity of soccer players’ representations. More specifically, we designed a soccer-specific coding scheme and we coded the complexity of soccer players’ verbalizations of the actions that took place in video clips they were exposed to. Our method, based on Skill Theory, thus allowed us to extract the complexity, regardless of the specific components that were verbalized (e.g., a player, the ball, the kind of action). For example, when a player in the clip gives a cross from the left, the soccer player may describe the action as “the player shoots”, which reflects a representation of a low complexity level, including the connection between two directly observable components (i.e., the player and the ball). However, the soccer player could also integrate several components of the action, such as the ball, goal, and players, as well as relative positions between these components, by stating: “The *left wingback* gives a cross to the *striker* at the *second post*”. In addition to the general interest to capture the complexity of cognitive skills of athletes, we specifically address whether the complexity level of the soccer game play representations, is related to the level of expertise of soccer players.

1.4 Capturing Complexity in Motor Performance (Chapter 3)

Whereas Chapter 2 is focused on complexity at the level of cognitive skills, assessed while athletes watched sports video clips, Chapter 3 examines the complexity of the motor system that generates actual sport performances. When performing bodily movements, various processes take place that contribute to how the movements are executed, including neuronal activity, muscle contractions, limb movements, and so forth. The processes involved in movement execution are not only numerous, but also coupled, and take place at different levels and time scales. This entails that motor performance emerges from continuously interacting component processes (i.e., interaction-dominant dynamics), which is opposed to the perspective that human performance is determined by localized functions or modules that command our movement sequence to be carried out, such as a central pattern generator or motor program (i.e., component dominant dynamics; see Wijnants, 2014).

Our assumption that sport performance—here motor performance in particular—emerges from interaction dominant dynamics (i.e., complexity) rather than component dominance, is based on two lines of reasoning that have been proposed in the literature. The first is that elite athletes' performance is, and should be, coordinated, yet flexible (Chow, Davids, Hristovski, Araújo, & Passos, 2011; Phillips, Portus, Davids, & Renshaw, 2012; Seifert, Button, & Davids, 2013). That is, even if movement patterns show regularities (e.g., in repeated rowing strokes), they are also adaptive (e.g., a rower can easily adjust his movements to speed up or react to a branch in the water). One principle hypothesis according to the interaction dominant perspective, is that the human motor system organizes itself around metastable states, meaning that it is placed in between order (regularity) and disorder (flexibility) (e.g., Kello, Beltz, Holden, & Van Orden, 2007; for a general theoretical model, see Bak, Tang, & Wiesenfeld, 1988). The second line of reasoning is of a statistical nature. If our motor performance is generated by separate components performing specific functions to generate our movements, we would expect that repeated movement measures (e.g., of movement duration) reveal random variations from measure-to-measure, called *white noise*. In other words, if each measure (e.g., the duration of a single rowing stroke) is the sum of independent component effects, and each subsequent movement is independent from the former, we should observe a normal distribution of measures with error variance on either side (cf. central limit theorem, see Kello et al., 2010). In reality, however, white noise in time series of human processes is the exception rather than the rule (Kello et al., 2007).

In the domain of physiology and motor control, white noise patterns are only observed in people who suffer from a (physiological or motor) disease (e.g., Goldberger et al., 2002; Hausdorff et al., 1997; 2001). Measuring healthy physical processes in real-time, researchers virtually always find that the pattern of variation is characterized by many high-frequency and low-amplitude fluctuations that are nested in low-frequency and high-amplitude fluctuations, which is called *pink noise* (or 1/*f* noise). This pink noise pattern would be a typical expression of complexity, as it would reflect that motor processes at faster time scales are nested in processes at slower time scales, and that all these processes interact cooperatively to generate our performance (e.g., Van Orden et al., 2003). In line with this reasoning, the time series of heart beat intervals of healthy adults reveal prominent patterns of pink noise, whereas a clear deviation from pink noise (e.g., random variation in intervals) signals heart failure (e.g., Goldberger et al., 2002). In addition, stride interval time series of healthy young adults reveal patterns of pink noise, whereas stride intervals of people with Huntington or Parkinson disease demonstrate white noise patterns (e.g., Hausdorff, 2009; Hausdorff et al., 1997).

Assuming that human physiology and motor control is characterized by complexity—physiological and motor processes take place across multiple time scales in interaction—, which is expressed in a pink noise time series, it is likely that time series of sport performance also reveal this pattern. In line with the fact that cyclical (i.e., repetitive) movements lend themselves best for the analysis of temporal structures (e.g., Glass, 2001; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009; Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012), Chapter 3 aims to examine the noise patterns in rowers' rowing strokes at ergometers. Furthermore, given the proposition that elite athletes' performance is characterized by movement patterns that are both regular and flexible (e.g., Chow et al., 2011; Phillips et al., 2012; Seifert et al., 2013), we test whether elite athletes' time series of ergometer performance reveal more prominent patterns of pink noise compared to the performance of sub-elite athletes.

1.5 Emergence of Positive and Negative Psychological Momentum in Teams (Chapter 4)

In the Chapters discussed above, we aim to capture complexity during tasks in which participants are not “perturbed”. In reality, however, individuals or teams often perform their actions to achieve specific goals, and along the way they encounter positive or negative events (i.e., the perturbations) that bring them closer to, or further away from, a desired goal. The psychological and behavioral performance changes, that occur while progressing or regressing in relation to a goal, can be studied within the dynamical framework of psychological momentum (PM; Gernigon et al., 2010).

In general, positive and negative PM have been considered as dynamic states that may emerge and disappear (Adler, 1981; Adler & Aldler, 1981; Gernigon et al., 2010). More specifically, according to the most recent definition, PM is “a positive or negative dynamics of cognitive, affective, motivational, physiological, and behavioral responses (and their couplings) to the perception of movement toward or away from either an appetitive or aversive outcome” (Gernigon et al., 2010, p. 397). The complex nature of PM is reflected in the various interacting cognitive, affective, behavioral, and situational components from which positive and negative PM emerge (Briki, Den Hartigh, Hauw, & Gernigon, 2012; Gernigon et al., 2010). In team performance, athletes are also involved in continuous interactions with their team members. During a competition, positive and negative PM thus emerge out of complexity (i.e., the interacting components).

A major challenge with regard to research on PM is to study its dynamical nature, that is, *how* positive and negative PM states actually emerge. To date, research on PM has mainly focused on the antecedents of PM (i.e., specific personal and situational components that may cause PM) and its consequences (i.e., performance changes) (e.g., Tayor & Demick, 1994; Vallerand, Colavecchio, & Pelletier, 1988), thereby limiting the understanding of the *emergence* of this complex phenomenon. Our suggestion that the emergence of PM is difficult to capture based on this conventional approach has been indirectly supported by a reviewer, who noted that “there are more factors that influence PM than researchers can count”. This also contributes to the idea that deeper insights into the PM process are unlikely to come from attempts to search for the additional influence of specific factors. To obtain a better understanding of PM dynamics, we should thus apply an alternative method, which allows us to examine the process, that is, *how* PM moves to its two forms (i.e., positive and negative PM).

About three decades ago, Haken et al. (1985) proposed a method to study how different coordination patterns form in biological systems, which I will briefly explain given its applicability to PM research. The HKB method was established based on an experimental research program to understand the emergence of different states of coordination in humans, as well as the conditions that give rise to the different states (for a review, see Kelso, 1995). The main purpose of Kelso and colleagues' research program was to come to an understanding of changes in coordination patterns with a parsimonious framework based on the following theoretical concepts and recommendations. First, many components can be experimentally studied (e.g., activations of different muscles or muscle groups), but according to the HKB method one should determine the essential variables (i.e., collective variables or order parameters) in order to characterize the coordination dynamics. The second methodological recommendation is that one should determine the variable (i.e., the control parameter) that induces a change from one coordinative state to another (Beek, Verschoor, & Kelso, 1997).

The first major insight based on the HKB method was that anti-phase (abduction-adduction) finger movements change to an in-phase pattern at some critical movement frequency (e.g., Haken et al., 1985; Schöner & Kelso, 1988). When the movement frequency decreased again, people remained in the in-phase pattern for some time, that is, a shift back to the anti-phase pattern was delayed, which is called hysteresis. In these studies the relative phase (i.e., the relative timing difference between the two fingers) was the collective variable, which captures the pattern emergence from the interactions among various neuronal, muscular, and metabolic components. The movement frequency was the control parameter that changes (but does not prescribe) the coordination pattern. By showing that an in-phase pattern is more stable (i.e., more easily maintained) than an anti-phase pattern, Kelso and colleagues concluded that the in-phase coordination pattern is a stronger 'attractor'—a state or pattern toward which the behavior tends to evolve—than the anti-phase pattern (Schöner & Kelso, 1988).

Recently, Gernigon et al. (2010) proposed that an adaptation of the HKB method is very well suited to study PM dynamics. In line with Gernigon et al.'s proposition, Chapter 4 specifically examines the dynamics of team PM by applying the principles of the HKB method. In line with these principles, the first question to be answered is which variables are essential to characterize team PM dynamics. First, because (team) PM involves both psychological and behavioral variables, we focus on collective variables in both spheres. At the psychological level, we take collective efficacy into consideration, which is considered one of the most powerful team attributes. Collective efficacy is not an aggregate of individual self-efficacies, but rather an emergent phenomenon on the group level that is related to PM, thereby qualifying as a suitable collective variable (Bandura, 1997; Tasa, Tagger, & Seijts, 2007). According to the literature on team performance, another essential and emergent team-variable related to PM is task-cohesion (Carron & Hausenblas, 1998; Eisler & Spink, 1998), which we therefore also take into account. At the behavioral level, the coordination between the team members' actions and the team efforts are typical team level variables that are critical for team performance (Kozlowski & Ilgen, 2006), and likely undergo changes when moving from positive to negative team PM and vice versa (Adler, 1981).

The second question is what variable induces a change from positive to negative team PM, that is, what could be the control parameter? According to earlier literature, PM would be triggered when perceiving progress or regress in relation to the outcome or goal one wants to reach (e.g., winning a match in sports; Gernigon et al., 2010; Vallerand et al., 1988). In line with the guidelines of the HKB method, the position in relation to a desired outcome or goal would qualify as a control parameter that can be varied (thereby manipulating progress and regress). Thus, taken together, Chapter 4 is inspired by the original HKB method and its proposed adaptation to study PM (Gernigon et al., 2010). In this chapter, we specifically examine team PM dynamics by studying *how* collective efficacy, task-cohesion, efforts, and interpersonal coordination change when rowing teams progress or regress in relation to the victory in an ergometer race.

1.6 The Interconnection Between PM Within and Across Task Performance (Chapter 5)

Although the previous literature focused on PM within a task or match (see Chapter 4), theorists have proposed that complex dynamical processes take place at several interacting levels and time scales (e.g., Newell et al., 2001). With regard to PM, this would mean that the PM dynamics within a task are probably embedded in a PM process that takes place over a longer time scale (i.e., over multiple tasks). In turn, the PM process that takes place on the longer term time scale, is influenced by the single tasks.

While empirical evidence is repeatedly found for the proposition that human physiological and motor processes emerge from interacting processes across multiple time scales (Chapter 2), interacting time scales with regard to social phenomena are mostly hypothesized in theoretical works (e.g., Granic & Patterson, 2006; Lichtwarck-Aschoff, Van Geert, Bosma, & Kunnen, 2008; Van Geert & Steenbeek, 2005). However, some empirical indications have been found in the domain of learning based on observations of natural student – teacher interactions. For instance, Steenbeek, Janssen, and Van Geert (2012) studied student – teacher arithmetic sessions and students' learning trajectories over a school year. They found that ineffective sessions (e.g., due to initiations of the student that are followed by (repeated) ineffective feedback or responses of the teacher) influence the quality of the student – teacher communication in the next session, and hence results in a suboptimal learning trajectory of the student over the course of the school year. In other words, the short term dynamics shape the long term learning trajectory, and the learning trajectory influences the student – teacher dynamics within (next) sessions.

In the domain of motor learning, Zanone and Kelso (1992) conducted an experiment in which they exposed individuals to a coordination task they had to learn (i.e., moving fingers in a 90° relative phase, which is a relatively difficult coordination pattern, see Haken et al., 1985; Kelso, 1995; Schöner & Kelso, 1988). The authors found that it was difficult for most participants to produce the pattern at the baseline session, before learning the coordination task. However, learning the task in single sessions (short-term) seemed to change the pre-existing preferred coordination patterns (i.e., the attractor landscape), which became visible when examining the coordination dynamics across sessions (longer-term). More specifically, Zanone and Kelso (1992) found that the participants learned to execute a 90° relative phase coordination in a fairly stable manner over the course of the experiment (i.e., five days). This suggests that the short term learning sessions altered the attractor landscape of possible coordination patterns that extended over the longer term (i.e., across sessions), which in turn constrained the performance of the coordination task within the next session (short-term).

Chapter 5 is based on the propositions that (a) processes involved in human performance take place across multiple time scales that are interconnected (e.g., Steenbeek et al., 2012), (b) pre-existing dynamics can be altered by performances in successive sessions (Zanone & Kelso, 1992), and (c) PM dynamics can be studied based on an adapted HKB method (see Chapter 4). In the first conceptualization of PM in the literature, Adler (1981) proposed that PM takes place within a task (e.g., a sports match), but also across tasks, such as during a sports tournament or season. Given that PM is considered a complex dynamical phenomenon (Gernigon et al., 2010), long- and short-term PM processes should be interconnected (cf. Steenbeek et al., 2012). Furthermore, because successive sessions may influence pre-existing dynamics, repeated successful or unsuccessful sessions should affect the PM dynamics within a subsequent session (cf. Zanone & Kelso, 1992).

Recent research on PM dynamics in individuals has shown that, within a competition, negative PM is entered more rapidly and is more stable than positive PM (i.e., negative PM is a stronger “attractor state”; Briki, Den Hartigh, Markman, Micallef, & Gernigon, 2013). Because dynamics can be altered by previous sessions or experiences (Zanone & Kelso, 1992), we propose that previous successful competitions leading to long-term positive PM could weaken the negative PM attractor within a subsequent competition. In Chapter 5 we experimentally test this question during an ergometer-rowing tournament, by (a) manipulating athletes’ successive races, which they could either win or lose, respectively, and (b) letting athletes gradually regress from an almost-victory to a defeat in the last session in order to study the PM dynamics within that race. The collective variables we take into account are the perceptions of momentum, self-efficacy, and the effort exertion of the athletes.

1.7 Emergence of Excellent Performance Out of Complexity (Chapter 6)

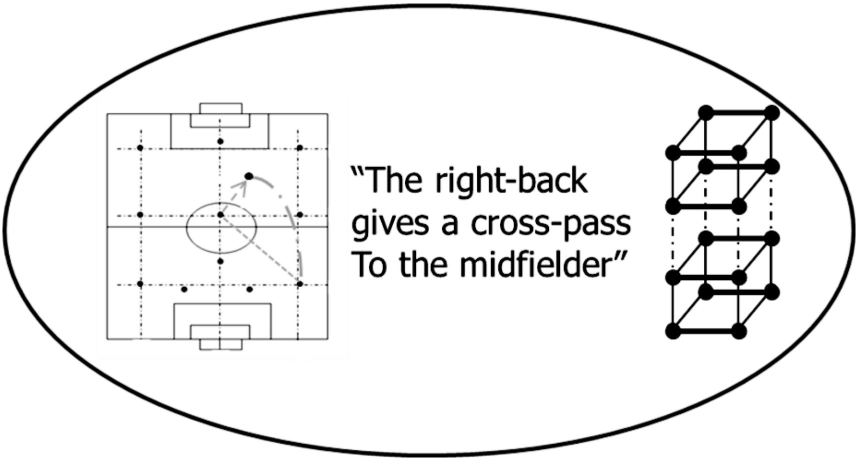
In the chapters outlined above, we aim to study complex dynamic processes on relatively short time scales (i.e., during task performance and across a few tasks). Such processes can often be examined within the specific context in which they take place. Processes developing over a long period of time are more difficult to capture based on observational and experimental research designs. However, researchers have shown that such processes can be investigated using computer simulations (e.g., Nowak, Szamrej, & Latané, 1990; Nowak, Vallacher, Tesser, & Borkowski, 2000; Schuhmacher, Ballato, & Van Geert, 2014; Van Geert, 1991). To date, one of the most challenging long-term processes to capture in relation to human performance is the development of excellence (Detterman, 2014; Kaufman, 2013). Since the 19th century, researchers and philosophers have attempted to find the components that underlie excellence development (Simonton, 1999). Currently, about 150 years later, the debate on the underlying components continues to exist (e.g., Detterman, 2014; Kaufman, 2013). In addition, major components that have been proposed previously, such as deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993), turn out to be not as important as previously assumed (Hambrick et al., 2014; Macnamara, Hambrick, & Oswald, 2014). In line with our complexity perspective on human performance processes, Chapter 6 proposes that excellence emerges out of mutual interactions between several performance-related components, such as one's ability, practice, family support, coach or teacher support, that form a dynamic network.

The central focus in Chapter 6 is to study the topology from which excellence develops. In general, a network topology can be envisioned as a graph characterized by several nodes, which correspond to the components (e.g., ability level, amount of practice) that are connected via a number of links. In the past decades, different kinds of network topologies have been proposed, and the ones that are applied most frequently are the random network (Erdös & Renyi, 1960), which formed the basis for more "real-world" network topologies, such as the small-world network (Watts & Strogatz, 1998) and the scale-free network (Barabási, 2009; Barabási & Albert, 1999). In a random network (Erdös & Renyi, 1960), couples of randomly selected nodes are connected, and each node has the same probability of being connected to any other node within the network. In a small-world network (Watts & Strogatz, 1998), most nodes are connected to their nearest neighbor nodes, whereas some nodes are randomly connected to more distant nodes in the network. Hence, this kind of network is characterized by a high clustering of components with some shortcuts to other (clusters of) components. Many real-world phenomena exhibit small world properties, such as the spread of rumors, epidemic diseases, or computer viruses (see Strogatz, 2003). In a scale free network (Barabási, 2009; Barabási & Albert, 1999), few nodes are connected to many other nodes, and a large number of nodes are poorly connected (hence generating a scale-free power law relationship between the number of links and the amount of components having that number of links). Scale free networks properties are found in, amongst others, the world-wide-web, protein interactions, and traffic dynamics (see Barabási, 2009).

Research on talent and excellence development has shown that an individual's ability is influenced by several components, including practice, parental support, coach and teacher support, and it is likely that such components in turn influence the individual's ability, either directly or indirectly (cf. Küpers, Van Dijk, & Van Geert, 2014; Van Geert & Steenbeek, 2005). In Chapter 6 we therefore simulate ability-networks including *directed* links between the nodes, which means that the connections run from one node to another. These connections are sparse and randomly assigned (cf. Erdös & Renyi, 1960), and each node has few direct links, but could be indirectly connected to a large portion of the other nodes (cf. Watts & Strogatz, 1998). Moreover, nodes (e.g., developing an interest in activities outside one's ability domain) may appear or disappear over an individual's (career) development and establish connections with other nodes (cf. Barabási, 2009). Although this network topology thus has similarities with existing network models that have been used to examine complex processes, it is tailored to the characteristics of human ability development.

In short, the network model we propose in Chapter 6 explains excellence as a developmental and emergent property. In a particular individual's ability network, a node could have a supportive effect on other nodes (e.g., a coach who stimulates the motivation and interest of a child), but it could also inhibit the development of another node (e.g., a tough coach who negatively affects the motivation and interest of the child). Thus, the network constantly develops through changes in the levels (i.e., values) of the nodes, among others as a consequence of the interactions with other changing nodes. In addition, the directed links between the components could be symmetric, asymmetric, direct, and indirect. We aim to demonstrate that this model, characterized as a network with dynamic properties, provides a basis to understand the process of excellence development. We will do so by showing the correspondence between the network model predictions and the existing literature on talent and excellence development.

Chapter 2: Characterizing Expert Representations During Real Time Action: A Skill Theory Application to Soccer



This chapter is based on:

Den Hartigh, R. J. R., Van Der Steen, S., De Meij, M., Van Yperen, N. W., Gernigon, C., & Van Geert, P. L. C. (2014). Characterising expert representations during real time action: A Skill Theory application to soccer. *Journal of Cognitive Psychology, 26,* 754-767. doi: 10.1080/20445911.2014.955

Abstract

In various domains, experts are found to possess elaborate domain-specific representations they developed over years. In this study, we provide the first systematic attempt to characterize short-term representations among individuals with different expertise levels. We showed videos of soccer game plays to expert, near-expert, and non-expert soccer players, and asked them to describe the actions taking place. Verbalizations were coded based on Fischer's Skill Theory. Monte Carlo permutation tests revealed that players with higher expertise constructed representations of higher complexity (regardless of their specific content). Taking the content of the representations into account, we found that higher-expertise soccer players relatively more often included high complexity levels of actions not including the ball and (moving) players on the field. These findings improve our understanding of perceptual-cognitive expertise, by demonstrating how actors with different levels of expertise integrate the information they perceive to construct their representations in real time.

2.1 Introduction

Within the domains of sports (Williams, 2000), medicine (Ericsson, 2004), and physics (Chi, Glaser, & Rees, 1982), experts are found to possess more domain-specific knowledge of facts and memories that they have developed over the years. While stored knowledge and memories refer to constituents of long-term representations, representations are also formed on the short-term (see Allan & Bickhard, 2013; Van Geert & Steenbeek, 2013). Such representations would, for example, refer to "reading" the game during a soccer match (e.g., Bjurwill, 1993), or the formation of scientific concepts during science class (e.g., Van der Steen, Steenbeek, Van Dijk, & Van Geert, 2014). These short-term representations emerge from the individual's interaction with the material (or social) environment in real time, and are thus different from how representations are constructed in long-term memory. More specifically, what occurs in a particular situation (e.g., in a class room, on a sports field) feeds into the short-term representation, which may leave memory-traces, and change the complex network of skills and knowledge that constitutes the long-term representation (Van Geert & Steenbeek, 2013).

Research suggests that the long-term representations that have developed over time lead to an increasing ability to retrieve particular situations or structures (e.g., chess play positions, players' positions on the soccer field), and consequently enhance anticipation skills (e.g., Ericsson & Kintsch, 1995; Feltovich, Prietula, & Ericsson, 2006; Van Geert & Steenbeek, 2013). Although long-term representations, as well as their possible relationships with domain-specific expertise have been investigated for decades, no attempt has yet been made to examine whether, and how, individuals with different domain-specific levels of expertise differ with regard to their short-term representations. In the current study, we propose Skill Theory, developed by Fischer (1980), as a framework to investigate and characterize these short-term domain-specific representations. We applied the framework in sports (i.e., soccer), a research area in which key insights into perceptual-cognitive skill development have been gained in the last decades (see Ericsson & Lehmann, 1996). An additional advantage of the domain of sports is that phenomena can be studied on a small surface and/or on a relatively short time scale.

Expertise and Long-Term Representations

Early evidence for the assumption that experts have extensive long-term domain-specific representations comes from De Groot (1946/1965), who observed that master chess players outperformed lower-level players in their ability to reconstruct a chess position after being briefly exposed to it for 5 seconds. De Groot (1946/1965) concluded that master chess players possess elaborate representations of chess plays, so that they rapidly recognize, and remember, the structuring of static chess positions to which they are exposed. This finding was later replicated by Chase and Simon (1973), who also suggested that expert chess players have developed a skill to recognize the structure of the chess piece locations, due to repeated exposure to different chess board positions.

Comparable results have been found in other domains, including soccer (e.g., North, Williams, Hodges, Ward, & Ericsson, 2009; Williams & Davids, 1995; Williams, Hodges, North, & Barton, 2006). Williams et al. (2006) presented expert and non-expert soccer players with offensive soccer action sequences; half of the sequences had already been presented to the players in an earlier viewing phase. The results of their first experiment showed that expert players recognized earlier shown sequences quicker and more often than non-expert players. In their second experiment, Williams et al. (2006) displayed the players on the field as point-light formats. That is, a series of white dots depicted the players' movements on a black background. Again, relative to non-expert players, expert soccer players recognized the similarity between the point-light sequences and the earlier encountered soccer sequences quicker and more often. In their interpretation of these results, Williams et al. (2006) suggested that expert players have more extensive (long-term) representations of patterns on the soccer field (Experiment 1), in particular with regard to players' positions in relation to each other (Experiment 2).

Perceptual-Cognitive Skills in Real Time

Although the above-mentioned studies focused on recalling or recognizing earlier encountered situations (e.g., chess positions or soccer film clips), researchers have also applied methods to untangle what information experts pay attention to during real time performance, for instance, by employing visual search paradigms and verbal report protocols. In visual search studies, several authors conducted eye-movement recordings of soccer players involved in anticipation and decision-making tasks (e.g., Helsen & Starkes, 1999; North et al., 2009; Roca et al., 2011; Vaeyens, Lenoir, Williams, Mazyn, & Phillaerts, 2007). Researchers found that, compared to non-experts, experts shifted their gaze more frequently toward the positions and movements of other players, as well as areas of free space, rather than (the player in possession of) the ball. Based on these results, researchers assumed that experts are better able to structure relevant, informative game elements into meaningful units, which enhances anticipation and decision-making. However, this assumption derives from indirect evidence (gaze fixations); a characterization of the actual cognitive structuring of the game elements (i.e., the short-term representation) was not provided.

Recently, Roca et al. (2011) added a verbal report protocol to their visual search method. Soccer players were presented with life-size video clips showing an attack of the opponent from a defender viewing perspective. They were then asked to retrospectively provide verbal reports on their thought processes during the clip. The authors found that experts evaluated the situation on the field more frequently, and provided more predictions and intentions for future actions, suggesting experts have more complex domain-specific representations (for another study combining visual search and verbal reports, see McRobert, Ward, Eccles, & Williams, 2011). Comparable findings have been revealed by McPherson and colleagues, who exclusively applied verbal protocols (e.g., McPherson, 1993; McPherson, 2000; McPherson & Thomas, 1989). For instance, after each point, McPherson (2000) asked tennis players about their thoughts when playing the previous point, and next, what they were thinking about at the current moment. McPherson (2000) also found differences related to evaluation and intentions for future actions, in the sense that expert tennis players reported a greater number and variety of goal concepts (the goal structure of the game, or means to win the game), condition concepts (when or under what conditions actions should be carried out to achieve the goals), and action concepts (rules for generating patterns to produce goal-related changes). Additionally, the sophistication levels of the concepts (i.e., reported details) were higher for experts, and they reported more connections and linkages between the concepts (experts used more words like ‘as’, ‘if’, ‘then’, ‘to’, ‘so that’, etc. within single phrases). However, Roca et al.

(2011) and McPherson and colleagues (McPherson, 1993; 2000; McPherson & Thomas, 1989) did not extract a measure reflecting the structuring, or complexity, of short-term representations.

To summarize, research methods based on visual search behaviors and verbal protocols have provided insights into what kind of information experts pay attention to, as well as how expert athletes retrospectively evaluate the situation more often, and plan future actions more extensively. Yet, focusing on separate gazes (e.g., Helsen & Starkes, 1999; North et al., 2009) or frequencies/counts based on retrospective evaluations and intentions (e.g., McPherson, 2000; Roca et al., 2011) does not provide information on the cognitive structuring of what the players actually see and how they integrate this information, which is assumed to be a key characteristic of the construction of short-term representations (Van Geert & Steenbeek, 2013). Moreover, because the participants' verbal reports were provided after the task (e.g., Roca et al., 2011) or in between intermittently played points (McPherson, 2000), the results could by definition not reflect the short-term representations the participants constructed in real time. For a systematic examination of short-term representations, it is thus necessary to have a framework allowing to score verbalizations while being exposed to real time actions, and to arrive at a single measure reflecting the complexity of the short-term representation being constructed.

Toward a Measure of Short-Term Representations

An individual's short-term representation within a domain can be viewed along two dimensions: (1) The dimension of content (e.g., a passing action of a soccer player), and (2) the dimension of complexity, that is, the integration of multiple actions and/or interconnected elements of the action (Van der Steen, Steenbeek, & Van Geert, 2012). To reliably investigate short-term representations, the theoretical framework within which they are studied should be able to take both dimensions into account. In the field of cognitive development, Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) is such a theory. Taking into account the continuous interaction between person and context, Skill Theory entails a framework for evaluating the cognitive complexity of the ways in which people organize their actions and thoughts (Fischer & Bidell, 2006). One of the most powerful characteristics of Skill Theory is that it can extract complexity from content, resulting in a content-independent measure of short-term representation levels. This means that the representations of the elements (e.g., player, ball, opponent in the case of soccer) and the connections between them can be assessed in a content-independent way, making it possible to evaluate the complexity of short-term representations in various fields. Because of this possibility to obtain content-independent measures, Skill Theory enables researchers to compare levels of representations across multiple time points, contexts, persons, and levels of expertise.

Skill Theory characterizes skills as thinking structures formed in a specific context, which can be a science class (Van der Steen, Steenbeek, & Van Geert, 2012), or another achievement context (see Fischer & Bidell, 2006). These thinking structures (e.g., short-term representations) can be assessed on a hierarchical scale ranging from low to high levels of complexity. The Skill Theory complexity scale consists of ten levels, divided into three tiers. The first tier refers to *sensorimotor skills*: Representing simple connections of actions on objects, events, or people in the world. The second tier refers to *representations*, which are knowledge structures reflecting components that are independent of specific observable actions, although based on them. The third tier refers to *abstractions*: General non-concrete rules that also apply to other situations. Within each tier a similar structure of four levels exists, reflecting an increasing complexity of the short-term representation. The first level begins with single sets, meaning single actions, single representations, or single abstractions. On the second level, these sets are coordinated so that they form relations between sets, called mappings. On the third level, these mappings are in turn coordinated so that they form relations between mappings, called systems. On the fourth level, systems are coordinated and form a system of systems, thereby reflecting a single set of a new type, the first level of the next tier.

Skill Theory has already been applied within educational contexts. For example, Van der Steen et al. (2014) examined interactions between a 4-years old child and a teacher, while working on different air pressure tasks—e.g., connecting two syringes with a transparent tube to explore the effect of air in this system—in three separate sessions. The authors showed that, compared to session 1 and 2, the child’s answers in session 3 more often reflected higher complexity levels. Furthermore, Yan and Fischer (2002, 2007) used a Skill Theory coding system to study how adults' representations changed when learning to use a computer program. They found that the participants' representations moved from fluctuating low complexity levels to higher complexity levels. These studies thus suggest that higher complexity levels of real-time representations emerge when developing expertise. However, to arrive at such a conclusion, two important steps remain to be undertaken: (a) conducting a systematic comparison of the construction of Skill Theory complexity levels between individuals with different levels of expertise, and (b) show that the relation between expertise and complexity is applicable to other contexts (i.e., outside of education).

The Current Study

In the current study, Skill Theory was applied in a sports context (i.e., soccer). The aim was to examine whether soccer players with different levels of expertise can be distinguished on the construction of their short-term game representations, as reflected by their scores on the Skill Theory complexity scale. In addition, we aimed to explore the complexity levels of the specific contents (i.e., type of soccer actions such as passing, and game elements such as the players). Therefore, a soccer-specific coding system based on Skill Theory was designed to code the verbalizations of soccer players while they watched soccer game plays (cf. Van der Steen et al., 2014; Van der Steen, Steenbeek, Wielinski, & Van Geert, 2012; Yan & Fischer, 2002; 2007). We used the coding system to identify the complexity levels of three groups of soccer players. These three groups participated in different leagues (i.e., professional league, national amateur league, and regional amateur league) that require different levels of expertise. Hence, soccer players participating in the professional leagues were considered as experts, whereas the national amateur league players were considered as near-experts, and the players from the regional amateur league as non-experts (cf. North et al., 2009; Roca et al., 2011; Williams et al., 2006). Given the suggestion that complexity levels of representations increase when developing expertise (e.g., Yan & Fischer, 2002; 2007), we expected that soccer players with higher levels of expertise would construct representations of higher Skill Theory complexity levels. Furthermore, since short-term representations not only have a complexity dimension, but also a content dimension, we examined content-specific differences among the three groups. That is, we assessed whether the higher complexity levels of players with higher expertise were particularly related to specific types of actions (e.g., actions of a player with the ball, such as outplaying, or actions not including the ball, such as a player's off-the-ball movements), and game elements (e.g., moving elements, such as the team members, or static elements, such as the goal). In this way, we explored additional factors distinguishing expert soccer players from those with less expertise.

2.2 Method

Participants

The participants were 28 Dutch male soccer players, aged 20-34 (M_{age} = 25.65, *SD* = 3.75), each belonging to one of the following groups: Experts, near-experts, and non-experts. The group of experts consisted of seven *professional* players (M_{age} = 27.71, *SD* = 4.75), who were active in their respective professional leagues in The Netherlands for 7.14 years (*SD* = 4.34). Four players were members of two different teams in the highest professional soccer league, and three players were part of a team in the second-highest professional league in the Netherlands. These three players also played in the highest national league in the years before the data collection, and their current team was ranked first in the second-highest league, which resulted in a promotion to the highest professional league a few weeks after the data collection. The group of near-experts consisted of 11 *national amateur* players (M_{age} = 23.90, *SD* = 3.88) from two teams of the highest amateur league in the Netherlands. On average, these players were active in this league for 5.00 years (*SD* = 3.92), and none of the players had ever played in a professional league. The group of non-experts consisted of 10 *regional amateur* players (M_{age} = 26.00, *SD* = 2.11) from two teams participating in the lower three amateur leagues in the Netherlands. These players were active in their current league for 4.90 years (*SD* = 2.23), and none of these players had ever played in the professional or national amateur leagues.

Participants were provided with an informed consent, and were free to withdraw from the study at any stage. Participation was voluntary, and participants were assured their contributions would be treated confidentially.

Procedure

The protocol of this study was approved by the Ethical Committee of the Department of Psychology, University of Groningen. The players targeted for the study were contacted either directly or through their clubs, and asked whether they would be willing to watch and describe some soccer game plays at a time that suited them. Appointments were made with the players who agreed to participate at their home soccer club. Participants were seated in front of a laptop, on which the video sequences were played. A video camera was placed at a 45° angle behind the participant to record his verbal reports. The participants were asked to watch three soccer game plays, and to describe (aloud) the actions taking place on the field. The researcher did not give any additional clarifications or points of attention, in order to keep the responses as authentic as possible.

Before the three game plays were shown, participants watched one practice sequence to check whether they (only) described the actions that took place on the field. A request to focus exclusively on the game-related actions was given to participants who described irrelevant elements, related to the supporters in the stadium (e.g., "there are many empty seats"), or the weather conditions (e.g., "it's cloudy") for example. After the practice sequence, the three soccer game plays were played successively with a break of 5 s between them, and were presented in a randomized order. Subsequently, all utterances were transcribed to facilitate the coding procedure.

Materials

The three videos to which the participants were exposed consisted of offensive game plays of 22 s, 17 s, and 34 s, which ended in a goal. The game plays were retrieved from matches played at the highest level in Ireland (IFA Premier League). They were recorded using a high-definition camera from an overview perspective (i.e., above the field), thereby providing a clear view of the field and the actions taking place. Only natural surrounding sounds of the game were broadcast, such as the indefinable noise from the players, crowd, and ball-kicking sounds.

None of the participants were familiar with the game plays or players, thereby ensuring the absence of familiarity advantages, such as knowing the outcome of the match or characteristic movements of particular players.

The Coding System

Based on Skill Theory, we developed a soccer-specific coding system for verbalizations consisting of seven complexity levels of game play representations (see Table 2 for an illustration of the different levels, from 1—single sensorimotor characteristics—to 7—single abstractions).[1]

We proceeded from the fact that the game of soccer consists of game elements (e.g., player, ball, team member), which are combined to form specific actions (e.g., the player passes the ball to the team member), and which are in turn combined to form specific game plays (e.g., combinations of passes and other actions in the offensive game play). A higher Skill Theory complexity level can be considered to be an increased, more complex representation of the interactions between the game elements and actions that unfold during the game play.

The verbalizations of the participants were coded in eight short phases. In the first phase, described soccer actions were separated, to form the basis for further analyses. Actions were chosen as unit of analysis, because game elements are usually meaningfully connected in actions. Actions were indicated by verbs representing a specific act (e.g., shooting, heading, passing), state (e.g., standing, having, looking), or occurrence (e.g., covering, getting). For instance, the following description, which we will use as an example, consists of four actions: "*Goal kick of the goalkeeper* (1: Kicking)*, Heads it through* (2: Heading)*, Puts it in front of the goal with the inside of his right foot* (3: Putting (the ball)), *And header into the goal* (4: Heading)".

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[1] The levels 8-10 were not taken into account, because these levels go beyond single abstractions, which is virtually impossible for this specific task (i.e., describing single game plays does not require linking multiple abstractions).

In the second phase, each of these separate actions was given a label. Out of the seven types of actions that could be distinguished, two types do not include the player with the ball: off-the-ball movements—a player who walks, stands, or runs on the field without the ball—(L), and defending actions (D). Four types of actions do include the player with the ball: Individual actions of a player with the ball—not including a team member or opponent—(B), passing actions—a player plays the ball to a team member—(P), actions of a player to individually outplay his opponent(s) (U), and scoring actions—a player attempts to score the goal—(S). The last category includes all other actions, such as looking or asking (O). The above-mentioned action description would thus be coded as follows: "*Goal kick of the goalkeeper* (B), *Heads it through* (P), *Puts it in front of the goal with the insight of his right foot* (P), *And header into the goal* (S)".

In the third phase, the game elements involved in each action description were labeled. Three types of game elements refer to the players on the field: The player (S), the player's team member(s) (M), and the player's opponent(s) (T). Two other game elements refer to the "static" elements that are present, which are the goal (D) and the field (V), and the sixth game element is the ball (B). The example would be coded as: "*Goal kick of the goalkeeper* (S,B), *Heads it through* (S,B,M), *Puts it in front of the goal with the insight of his right foot* (S,B,M,D), *And header into the goal* (S,B,D)".

In the fourth phase, we counted the number of actions that were related or coupled in the action descriptions. This is the case when a relation is made between two actions taking place at the same time (e.g., "<u>The striker heads back</u> (1) to the <u>incoming midfielder</u> (2)"), or when two actions are related that follow each other in time (e.g., "<u>The player moves in front of the defender</u> (1), so that <u>he can score</u> (2)"). When two or more actions were coupled, a higher complexity level was assigned, because this coupling represents a more comprehensive view of the action (cf., McPherson, 2000; McPherson & Vickers, 2004). Our example description does not include such a coupling between actions.

In the fifth phase, a score was given for the complexity of each action based on the Skill Theory complexity scale (Fischer, 1980). Actions, such as scoring, can be described in a relatively simple way (e.g., "a shot"), but also in a more specific way indicating the position of the foot while shooting the ball (e.g., "an instep kick"), or indicating the movement(s) of the body while shooting (e.g., "a volley"), or a combination of these two, including an indication of how this influences the path of the ball (e.g., “a chip”). Mentioning one or two extra observable details was considered level 2 or 3, respectively (sensorimotor system levels), whereas statements indicating an understanding of not directly observable relations were considered level 4 (single representation level), or higher. In our example, all action descriptions involved directly observable details: “*Goal kick of the goalkeeper* (1), *Heads it through* (1), *Puts it in front of the goal with the insight of his right foot* (2; the insight of the right foot provides an extra observed detail of the way the ball was passed), *And header into the goal* (1)”.

In the sixth phase, a score was given for the number of (connected) game elements in each action description. Descriptions of actions including more game elements indicate a more comprehensive view of the action, and were rewarded with a higher score. “*Goal kick of the goalkeeper* (2 elements; S,B), *Heads it through* (3; S,B,M), *Puts it in front of the goal with the insight of his right foot* (4; S,B,M,D), *And header into the goal* (3; S,B,D)”.

In the seventh phase, a Skill Theory complexity score was given for the way game features were described in each action description. For example, a “player” can be described as “the player on the left”, which gives extra (yet observable) information about the player’s position on the field, and was therefore assigned a sensorimotor mapping (level 2) score. On the other hand, the term “the left wingback” reflects an understanding about the player’s position that is not directly observable, but derived from information about the player’s position on the field in relation to the positions of other players. Statements like these were assigned a single representation (level 4) score. In our example, all game elements were described at level 1 (simple, observable information).

In the eighth phase, a final Skill Theory complexity level was assigned to each full action description. This overall complexity level consisted of the highest complexity level scored in the previous phases. However, if within an action description the same level was used twice, this would indicate a qualitatively higher understanding of the action, which was rewarded with a higher complexity level. For example, if within a single action description a level 4 (single representation) was given twice (e.g., “rebound” to indicate the type of action, and “number 10” to indicate a player; see Table 3), this would mean that the player described the action using a mapping of representations (level 5). This did not occur in our example, thus, based on the different coding phases, the actions were assigned the following overall complexity levels: "*Goal kick of the goalkeeper* (2), *Heads it through* (3), *Puts it in front of the goal with the insight of his right foot* (4), *And header into the goal* (3)". Finally, to represent the complexity of the entire game play description, we calculated the mean of the action descriptions. This number, representing the way in which all the actions and game elements were integrated, served as the main unit of analysis.

Reliability of the Coding System

Based on several pilots with soccer players of different levels, a researcher with experience in designing Skill Theory coding books constructed the coding system together with a soccer player. The reliability of the coding system was assessed using a percentage of agreement [(number of same findings) / (number of same findings + number of divergent findings)] between two coders. They coded nine descriptions given by participants, chosen randomly from among the 84 described videos. The agreement rate was 97.96% for the types of described actions; 91.84% for the complexity levels of the soccer actions; 100% for the number of (connected) game features; 98.68% for the types of game features; 93.88% for the complexity levels of the game features; and 93.88% for the overall complexity levels of the game play descriptions.

Table 2. Illustration of Skill Theory complexity levels in soccer.

Complexity level	Description
1: Single sensorimotor characteristics	Single observable characteristics of game features or actions that are not related to any other game feature or action *(The player runs)*.
2: Sensorimotor mappings	Observable relations between game features or actions *(The player kicks the ball)*.
3: Sensorimotor systems	Observable causal relations between game features or actions *(The player passes the ball to his team member)*.
4: Single representations	Not directly observable characteristics of game features or actions *(The player gives a cross pass)*.
5: Representational mappings	Relations between not directly observable characteristics of game features or actions *(The player gives a cross pass to the left wingback)*.
6: Representational systems	Relations between three or more not directly observable characteristics of game features or actions *(The left wingback gives a cross pass to the striker)*.
7: Single abstractions	Holistic inference of the interactions between the actions and game features during the game play *(They play kick and rush soccer)*.
0: Error	“Wrong” game features or actions in the game play *(The striker shoots;* while it was the left forward that placed the shot).

Data Analysis

To test whether soccer players with higher levels of expertise would construct short-term representations of higher Skill Theory complexity levels, participants of each of the three groups (i.e., experts, near-experts, and non-experts) were given a score for overall Skill Theory complexity level over the three game play descriptions.

Differences in complexity levels between the groups were tested with Monte Carlo permutation tests. Monte-Carlo tests outperform traditional parametric (e.g., ANOVA) and nonparametric tests (e.g., Kruskal-Wallis) in the case of relatively small sample sizes and/or unbalanced data sets (e.g., Ludbrook &

Dudley, 1998; Manly, 1997; Roff & Bentzen, 1989; Todman & Dugard, 2001; Van Geert, Steenbeek, & Kunnen, 2012). Contrary to ANOVA, the non-parametric Monte-Carlo procedure does not assume any underlying distribution or a minimum sample size, and one of its characteristics is that it has great discriminatory value in the case of smaller sample sizes and different group sizes in the study (e.g., Good, 1999; Lundbrook & Dudley, 1998; Manly, 1997; Todman & Dugard, 2001; Van Geert et al., 2012). The Monte Carlo test determines the probability that an observed result is caused by chance alone, by simulating that chance. To test whether experts have a more complex representation than near-experts, who in turn construct a more complex representation than non-experts, we shuffled the scores of all participants' overall complexity scores to obtain a redistributed set of scores; this was repeated 10,000 times. Then, we determined the probability (combined *p*-value; higher complexity for experts than for near-experts, *and* higher complexity for near-experts than non-experts) that the randomly redistributed scores would show results equal to, or more extreme than, the results we observed. If the *p*-value was low ($p < .05$), we could conclude that the observed results were unlikely to be caused by chance alone. To determine the magnitude of the observed outcome, we provided an estimate of the effect size by calculating Cohen's *d* (observed result divided by the pooled SD). According to the guidelines of Cohen (1988), a *d*-value of .2 to .3 is considered as small, around .5 as medium, and .8 or higher as large.

Regarding the exploration of complexity levels of specific contents of the game play, we focused on the separate actions and game elements. First, we calculated the proportion of *representations* per type of action (complexity levels 4-6) for each group to assess whether players with higher levels of expertise described particular types of actions (e.g., player with the ball, actions not including the player with the ball) relatively more often at high complexity levels. Second, we assessed whether players with higher levels of expertise described particular game elements (e.g., the players on the field) relatively more often at high complexity levels. Therefore we calculated a proportion score for representations per type of game element for the participants in each group. Again, differences between the groups were tested with Monte Carlo permutation tests.

2.3 Results

Preliminary Results

First, we examined differences among the three groups on other variables than the leagues in which they were playing. We found no significant differences with regard to age ($p > .05$). In addition, the groups did not significantly differ in terms of the number of active years in their current league ($p > .05$).

Skill Theory Complexity Levels

Table 3 displays three examples of a game play description of one soccer player from each group (expert, near-expert, and non-expert). This table also illustrates how we constructed a (final) complexity level for game play descriptions based on the different coding phases, and independent of the specific content of the descriptions. Based on this procedure, taking the mean complexity levels of all participants in each group into account, we found that the complexity level of expert players ($M = 4.03$, $SD = .23$) was higher than for near-experts ($M = 3.89$, $SD = .24$), who scored higher than non-experts ($M = 3.48$, $SD = .30$). The Monte Carlo results showed that the combined *p*-value was significant ($p_{combined} < .001$, $d = 1.66$). These results support our hypothesis, and indicate that it is highly unlikely that the results we found—complexity level of experts is higher than of near-experts, who in turn score higher than non-experts—can be caused by chance alone.[2] In line with the guidelines of Cohen (1988), the effect size (> .8) can be considered as large.

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[2] Earlier researchers particularly analyzed the number of described actions or contents involved in game plays (e.g., McPherson, 2000; Roca et al., 2011). The counts of described actions and game elements also revealed significant differences between the three groups in the current study, although less striking than the differences in the complexity scores.

Table 3. Illustrations of three game play descriptions; how the complexity levels are constructed and analyzed according to their real time expressions; and the overall complexity levels based on the structuring of the game elements and actions during the game play.

Phase:	1	2	3	4	5	6	7	8
Expert player	Long goal kick of the keeper [type of pass] to the side of the field	P	SBMV	1	4	4	1	5
	Conquered by the striker	B	SBT	1	1	3	4	4
	Rebound by number 10	P	SBM	1	4	3	4	5
	Plays it to the striker on the side	P	SBMV	1	1	4	4	5
	Striker puts it in front of the goal	P	SBMD	1	1	4	1	4
	And number 10 can head in	S	SBD	1	1	3	4	4
								4.50
Near-expert player	Long goal kick [type of pass] of the goalkeeper	P	SBM	1	4	3	1	4
	Defense at one line	V	SM	1	4	2	1	4
	Rebound	P	SBM	1	4	3	1	4
	Plays it through	P	SBM	1	1	3	1	3
	At the second post, a player is uncovered	L	SD	1	4	2	4	5
	Heads into the goal	S	SBD	1	1	3	1	3
								3.83
Non-expert player	Goal kick of the goalkeeper	B	SB	1	1	2	1	2
	Heads it through	P	SBM	1	1	3	1	3
	Puts it in front of the goal with the inside of his right foot	P	SBMD	1	2	4	1	4
	And header into the goal	S	SBD	1	1	3	1	3
								3.00

Note. Phase 1 = separating actions; phase 2 = labeling actions (P = passing, B = individual action with the ball, S = scoring, V = defending, L = off-the-ball); phase 3 = labeling game elements (S = player, B = ball, M = teammate, V = field, T = opponent, D = goal); phase 4 = number of (coupled) actions; phase 5 = skill theory level assigned to the action; phase 6 = number of game elements within the action; phase 7 = skill theory level of game elements; phase 8 = final complexity level of each action description, and calculating mean complexity level (in bold).

Separate Actions and Game Elements

Figure 1 displays the within-group proportions of high complexity levels (level 4 or higher) for each specific action. The figure shows that the higher the level of expertise of a player, the higher the proportion of high-complexity descriptions that contain the actions excluding the player with the ball (off-the-ball-movements and defending actions), and consequently, the lower the proportion of descriptions that contain a player in possession of the ball (action of player with ball, passing, outplaying and scoring). Specifically, the mean of proportion score for 'off-the-ball-movements' and 'defensive actions' together was highest for experts (M_{prop} = .37) and lowest for non-experts (M_{prop} = .18); the near-experts scored in between (M_{prop} = .24). Monte Carlo analyses revealed that the differences among the three groups were significant ($p_{combined}$ < .001).

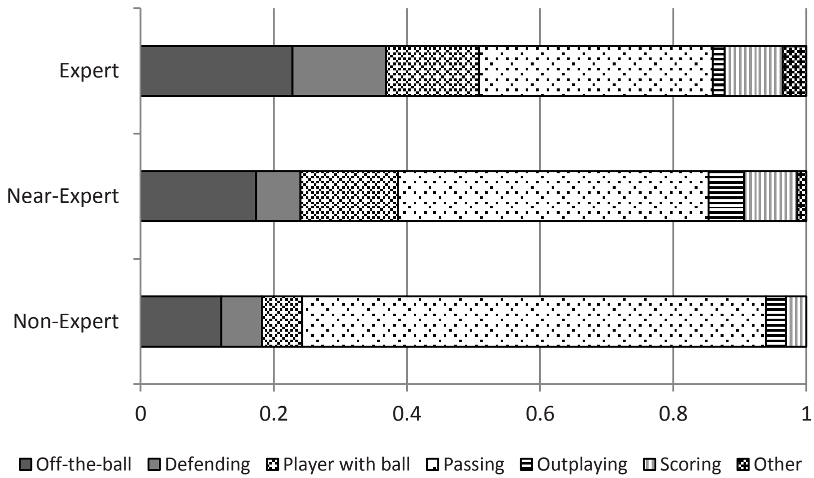


Figure 1. Proportions for high complexity levels (level 4-6) of the different types of described actions, according to level of expertise. The solid filled sections correspond to action categories excluding the player with the ball.

Figure 2 displays the within-group proportions of high-complexity descriptions (level 4 or higher) for the separate game elements. The figure shows that players with higher expertise described particular game elements relatively more often at high complexity levels. That is, the higher the level of expertise of a player, the higher the proportion of high-complexity descriptions for the "moving" game elements, i.e., the players on the field (player, team members, and opponents), and the lower for "static" game elements (goal and field). Monte Carlo tests indicate that the proportion of high-complexity descriptions for the (moving) players on the field was higher for experts (M_{prop} = .74), than for near-experts (M_{prop} = .67), who had a higher proportion than non-experts (M_{prop} = .23). Monte Carlo analyses revealed that the differences between the groups were significant ($p_{combined}$ < .001).

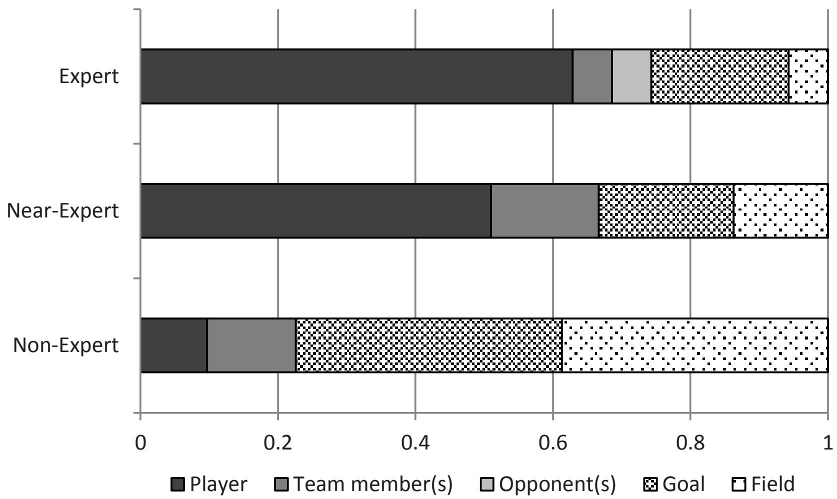


Figure 2. Proportions for high complexity levels (level 4-6) of the different types of described game elements, according to level of expertise. The solid filled sections correspond to the moving game elements (the players). High complexity levels for the ball were not included in the graph, because a ball is always described at sensorimotor level (i.e., a directly observable characteristic, often just "the ball").

2.4 Discussion

The aim of this study was to examine short-term representations as constructed in real time, and in particular whether increasing levels of soccer expertise would accompany higher complexity levels of soccer-specific game representations. To answer this question, verbal reports of soccer sequences generated by expert (professional), near-expert (high amateur), and non-expert (low amateur) soccer players were compared, using a coding system that distinguishes different complexity levels of short-term representations. In this way we were able to demonstrate at what complexity level players with different levels of expertise integrate, or structure, the actions and elements they pay attention to.

Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) provides a useful framework to examine the constructions of real-time representations, regardless of the specific content of the representations. Based on our soccer-specific coding system, we found that higher levels of expertise were associated with higher Skill Theory complexity levels of short-term representations. Thus, the short-term game representations of soccer players with higher levels of expertise are reflected in their ability to integrate the information on the field at higher complexity levels. This is in line with the claim that cognitive expertise involves a process of increasing complexity (Fischer & Bidell, 2006). Moreover, this indicates that players with high levels of expertise not just extract more (task-specific) information from the game play than low-skilled players, as was found in previous studies (cf., McPherson, 2000; Roca et al., 2011), but that they also structure this information differently, at higher complexity levels.

The credibility of these results and the sensitivity of our method are strengthened by the fact that all participants were soccer players participating in official competitions, and that we did not only include experts and non-experts, but also a group of near-experts. In contrast, other studies examining representations typically involved only pronounced differences in expertise between groups. For example, in the study by McPherson (2000), a group of experts was included, consisting of players with outstanding junior tennis rankings, and a group of non-experts containing novices participating in a beginner's tennis class.

Another interesting finding that emerged from our analysis is that players with higher levels of expertise described actions not including the player with the ball relatively more often at high levels of complexity than players with lower levels of expertise. This result can be considered in line with earlier findings from visual search paradigms, showing that expert soccer players more frequently shift their gaze away from (the player in possession of) the ball to other cues, such as the positions and movements of other players and areas of free space (e.g., Helsen & Starkes 1999; North et al., 2009; Roca et al., 2011; Vaeyens et al., 2007). However, our results also extend these findings by addressing *how* players with higher levels of expertise oversee, or integrate, the off-the-ball movements and defending actions. That is, visual search results indicate which actions participants attended to, but they do not reveal whether, and how, players with different levels of expertise integrate relationships between multiple sources of information to form their representation of the actions they notice. Using the Skill Theory complexity scale, we could specifically account for this (e.g., noticing that a player "sprints"—sensorimotor level—does not mean that a participant sees that the player "chooses position"—representational level).

Furthermore, we found that, relative to players with lower levels of expertise, players with higher levels of expertise described the players on the field relatively more often at high complexity levels. High complexity levels for players on the field mainly correspond to positional indications based on the orientations of the (described) player in relation to other (moving) players. Researchers working on recall and recognition tasks have already suggested that experts generally use relational information more effectively in the decision-making process, such as the players' positions on the field and/or the relative movements between the players (e.g., North et al., 2009; Williams et al., 2006; Williams & Davids, 1995). Our results support these authors' view that the ability to integrate relational information is an important characteristic of experts.

Theoretical and Practical Implications

While early researchers (Chase & Simon, 1973; De Groot, 1946/1965) already assumed the importance of cognitive expertise in terms of stored (long-term) representations, no attempts have been made to measure complexity levels of short-term representations as they are constructed in real time. In this study, we showed that higher levels of expertise accompany higher complexity levels of representations formed when players are exposed to soccer game plays. These insights can have significant implications for future approaches to perceptual-cognitive skills. In achievement contexts (whether in education or sports), decision making and anticipation also take place in real time. Rather than relating decision making and anticipation skills to representations stored in long term memory, which is the dominant approach (e.g., Ericsson & Kintsch, 1995; Helsen & Starkes, 1999; McPherson, 2000; North et al., 2009; Roca et al., 2011), the direct mechanism, or process, underlying superior anticipation and decision making of experts may be their superior ability to notice the patterns of ongoing interactions among the various elements during game plays. This suggestion could be further explored in future research.

Zooming in on the contents of the short-term representations, the results on the complexity levels of specific action or game element descriptions extend earlier results of visual search studies, as well as recall and recognition studies. That is, the results reveal at what complexity level players with different expertise integrate, or structure, particular action(s) and elements they pay attention to.

From an applied perspective, our outcomes may also have direct implications. We showed that characteristics of short-term representations can well be examined within the framework of Skill Theory. Part of this theory's appeal is that designing and applying a Skill Theory coding system is inexpensive and relatively easy. Indeed, its user friendliness has already been evidenced in the field of education, where a percentage of agreement of over 75% was observed between researchers and untrained teachers (see Dawson-Tunik, 2006). Furthermore, it can be applied using recordings of natural situations, without placing any burden on the recorded participants (Van der Steen, Steenbeek, & Van Geert, 2012). This is a great advantage compared with more time-consuming and costly techniques used in the domain of perceptual-cognitive expertise, such as eye-movement recordings, which are also hard to employ in natural situations.

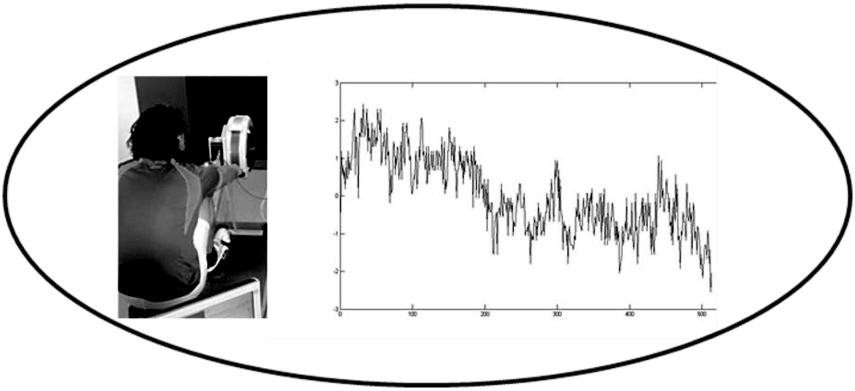
Limitations and Future Directions

The way participants (or people in general) are exposed to information could influence the way they construct their representations. For instance, it has been suggested that expert soccer players pay even more attention to their team members and opponents when they are presented with a player (ground level) viewing perspective (Mann, Farrow, Shuttleworth, and Hopwood, 2009), as opposed to the aerial viewing perspective that we used in this study. To advance insights into the ongoing construction of short-term representations, future research could therefore examine participants' representations using different viewing perspectives, including the actual player perspective.

Another interesting point for future research is to examine how the complexity of short-term representations develops over time, e.g., from a non-expert pattern to an expert pattern. Related to this, it would be fruitful to test how feedback from the coach, teacher, or manager affects individuals' construction of real-time representations. Fischer and colleagues already identified developmental ranges for domain-specific representations. Such a developmental range entails that the highest complexity level of a person under low support conditions (functional level) can be extended several steps upward when support of an expert is offered in the form of a social scaffold offering suggestions (optimal level) (e.g., Fischer & Bidell, 2006; Van Geert & Steenbeek, 2005).

Finally, as explained in the introduction, short term representations that are constructed during real-time action may leave memory-traces, and change the knowledge base (i.e., long term representations) that constitutes the long-term representation (Van Geert & Steenbeek, 2013). While long-term representations have been used as a causal mechanism for anticipation and decision making, future research should explore whether, in real time, anticipation and decision making emerge directly from the perception of interacting game elements during game plays.

Chapter 3: Pink Noise in Ergometer Rowing: Sport Performance Likely Emerges from Complexity



This chapter is based on:

Den Hartigh, R. J. R., Cox, R. F. A., Gernigon, C., Van Yperen, N. W., & Van Geert, P. L. C. (in press). Pink noise in rowing ergometer performance and the role of skill level. *Motor Control*.

Abstract

The aim of this study was to examine the temporal structures of rowers' (natural) ergometer strokes in order to make inferences about the underlying motor organization. Furthermore, we examined the relation between these temporal structures and expertise-level. Nine rowers, being part of one elite and one sub-elite rowing team, completed 550 strokes on a rowing ergometer. Detrended Fluctuation Analysis was used to quantify the temporal structure of the intervals between force peaks. Results showed that the temporal structure differed from random, and revealed prominent patterns of pink noise for each rower. Furthermore, the elite rowers demonstrated more pink noise than the sub-elite rowers. The presence of pink noise suggests that rowing performance emerges from the coordination among interacting component processes across multiple time scales. The difference in noise pattern between elite and sub-elite athletes indicates that the complexity of athletes' motor organization is a potential key characteristic of elite performance.

3.1 Introduction

Sport scientists have recently proposed that major advances can be made when considering sport and motor performance as emerging from complex systems interactions (Davids et al., 2014; Seifert et al., 2013). In this sense, coordinated actions such as rowing strokes would emerge from continuous interactions between motor processes at different levels and time scales (cell activity, muscle contractions, limb movements, etc.), embedded in (and shaped by the constraints of) the environment (Davids & Araujo, 2010; Seifert et al., 2013). In the domain of motor control, researchers have demonstrated that the temporal structure of performance variation may provide fundamental insights into the nature and effectiveness of the human motor system (e.g., Glass, 2001; Goldberger et al., 2002). For instance, random variation in stride intervals signals a higher risk of falling among elderly, whereas "healthy" stride intervals involve an appropriate ratio between rigidity and random variation (e.g., Goldberger et al., 2002; Hausdorff et al., 1997, 2001). Researchers have suggested that the latter type of "noise" reveals the presence of complex network interactions across brain and body, which means that motor control is distributed over cooperative processes at different levels of the motor system (for a review, see Wijnants, 2014). Although the complex systems perspective is gaining popularity in sport sciences, and researchers assume that effective or skilled sport performance requires a form of functional variability (i.e., between rigidity and random; see Davids, Glazier, Araújo, & Bartlett, 2003; Phillips et al., 2012; Seifert et al., 2013), empirical studies focusing on the temporal structures in sport performance are scarce.

The study of temporal structures of variation (i.e., noise patterns) and its meaning has a relatively long history in physical sciences (e.g., Bak et al., 1987, 1988), and has gained popularity in the domains of cognitive sciences and motor control in the past two decades (e.g., Gilden, Thornton, & Mallon, 1995; Goldberger et al., 2002; Hausdorff et al., 2001; Van Orden, Holden, & Turvey, 2003; Wijnants, 2014). Overall, three types of temporal structures can be distinguished, which lie on a continuum from white noise to brown noise (see Figure 3). White noise corresponds to purely random variation, and is assumed to be typical for component dominant systems (Van Orden et al., 2003). In the domain of motor control this would mean that the temporal variability in an action sequence is generated by random fluctuations in the component-processes (e.g., central pattern generator or motor program), resulting in an uncorrelated time series (Figure 3A; see also Diniz et al., 2011; Gilden, 2001; Van Orden et al., 2003; Wijnants, 2014). Brown noise corresponds to a stochastic function where each subsequent measure is relatively close to each preceding measure, which is assumed to be typical for systems composed of components that are tightly mutually connected. More specifically, each subsequent action is a function of the previous action to which a random increment is added, characteristic of a rigid pattern of behavior. Brown noise is reflected in time series by short-range correlations between sequential actions (Figure 3C; see also Gilden, 2001; Van Orden et al., 2003). In between white noise and brown noise lies pink noise, which expresses a subtle mixture of randomness and rigidity. Pink noise would be typical for interaction dominant (complex) systems (e.g., Glass, 2001; Van Orden et al., 2003; Wijnants et al., 2009; Wijnants, 2014). Because of the mutual interactions between flexibly coupled system components across multiple time scales, time series of interaction dominant systems behavior would display long-range dependencies between sequential actions (Figure 3B).

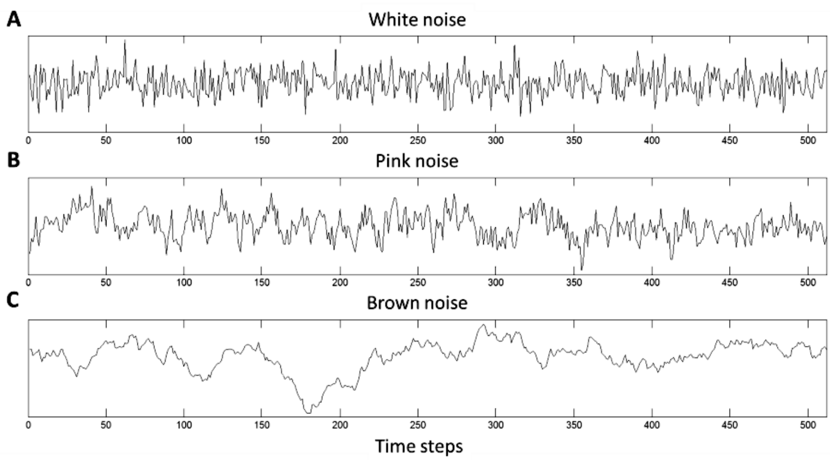


Figure 3. Three types of temporal structures of variation: White noise (A), pink noise (B), and brown noise (C).

Although applications of nonlinear time-series techniques to reveal temporal structures are in their infancy in sport sciences (Kuznetsov, Bonette, & Riley, 2014), signatures of non-random temporal structures have already been found in running and cycling performance (Hoos, Boeselt, Steiner, Hottenrot, & Beneke, 2014; Tucker et al., 2006). Hoos et al. (2014) studied fluctuations in speed, stride frequency, and stride length of long-distance runners during a half-marathon competition race, whereas Tucker et al. (2006) examined fluctuations of power output while cyclists were performing maximally during a time trial on cycle ergometers. To summarize, both studies reported non-random temporal patterns in performance variation (i.e., signatures of brown and pink noise).

However, Hoos et al. (2014) and Tucker et al. (2006) examined athletes' performance in competitive situations, which may have acted as an additional constraint on the control of the athletes' movements. Indeed, according to the authors, the noise patterns they found would be typical for athletes' pacing during a competition or time trial. This implies that the situations in which the participants performed probably affected the motor system by "pushing" it into a more rigid organization, thereby eliciting signatures of brown noise. As indicated earlier, research outside sports has shown that time series of natural and healthy motor performance exhibit prominent patterns of pink noise, characterized by an optimal mixture of randomness (i.e., flexibility) and rigidity (e.g., Glass, 2001; Goldberger et al., 2002; Hausdorff et al., 1997, 2001; Wijnants, 2014). Therefore, the first aim of the current study was to examine athletes' temporal structures of performance during a sport task in which additional (competition) constraints were not imposed. More specifically, we investigated the temporal structures in time series of rowers' ergometer strokes, which were performed at their preferred rhythm. Finding pink noise would provide evidence for the notion that the natural control of rowing strokes emerges from complex systems interactions (cf. Glass, 2001; Van Orden et al., 2003; Wijnants et al., 2009).

Furthermore, research outside the field of sports has shown that temporal structures of variation are closer to pink noise if the motor skill is better mastered. In a study on rhythmical aiming, Wijnants et al. (2009) found patterns of pink noise in time series of well-mastered aiming movements, suggesting that a high coordinative functioning between motor components had developed. When aiming movements were less well-mastered the authors found a whitening of the structure of performance variation, which suggests less coordination between the system components. Thus, our second aim was to examine whether a relationship exists between temporal structure of performance variation and level of rowing expertise. For this aim, we tested whether the temporal structures of variation in (natural) ergometer rowing strokes are closer to pink noise for elite rowers than for sub-elite rowers.

Finally, we chose for rowing on ergometers as a research setup, because this allowed detailed and reliable time serial measurements. In addition, because cyclical (i.e., repetitive) movements lend themselves well for the analysis of temporal structures (e.g., Glass, 2001; Wijnants et al., 2009; Wijnants, Cox, et al., 2012), this setup was highly suitable for obtaining insights into temporal structures of variation in sport performance.

3.2 Method

Participants

Nine competitive male rowers (M_{age} = 19.11, *SD* = .78) signed an informed consent form and a medical health form before the start of the study. All participants were members of the same rowing club. They started rowing 7 months earlier, and practiced three times a week in the period of this study, but up to five times a week in the period preceding the study. The participants were part of two different teams, which we distinguished based on the results of early-season competitions for first-year students. Five participants were part of a team ranked between 50% and 66.67% nationally (Team A: Sub-elite), and four were part of a team listed among the best 16.67% nationally (Team B: Elite). Note that the terms “sub-elite” and “elite” are relative to the category of (Dutch) first year’s rowers, specifically with regard to the attained levels of performance in the rowing season.

Measures and Procedure

The research protocol was approved by the Ethical Committee of the Department of Psychology, University of Groningen. For the experiment we used Concept 2 ergometers, Model E (Inc., Morrisville, VT). Between the handle and the chain of the ergometer, a force sensor (MEAS, France) was attached, which was connected to a data acquisition (DAQ) device (NI USB-6009). The DAQ device served to transfer the raw signals to a computer via USB, and these signals were collected in Volts (V) at a frequency of 100 Hz.

Each participant arrived individually for his ergometer session. After the participant did his warm-up activities, we instructed him to perform 550 strokes. This number was chosen in consultation with a coach of the participants' rowing club, who indicated that a rowing session that takes more than 30 minutes would be a burden for the rowers. A sequence of 550 strokes would last between 20 and 30 minutes (depending on the participant's stroke frequency), and would provide a sufficient amount of data points to perform reliable analyses (see analysis section). We asked the participant to perform the strokes at his preferred rowing rhythm. Moreover, we set the drag on the ergometer to 120, which corresponds to the resistance set by the participants for their usual workouts.

Analysis

The obtained time series data (in V) were first low-pass filtered with the Butterworth filter (cut-off frequency 8 Hz). The time intervals between the force peaks (maximal force in each stroke) were calculated and formed the unit of analysis. This measure was chosen because the coordination of force exertion is crucial for rowing performance (Hill, 2002; Wing & Woodburn, 1995).

Detrended Fluctuation Analysis (DFA; Peng et al., 1993), which is particularly suited for non-stationary data and relatively short time series (512 data points in the current study; stroke 18 to 530), was applied to each participant's peak-to-peak interval series. The result of DFA analysis reveals the relation between window size of data and the mean fluctuation of the windowed data. More specifically, the time series of intervals between force peaks were divided into non-overlapping windows of equal length. The best-fitting trend line was then determined and the average fluctuation (root mean square residual) was calculated. This procedure was repeated for windows of different sizes, ranging from a subset of 4 interval-data points to 128 interval-data points (i.e., ¼ times the length of the entire series we analyzed). The relationship between the average fluctuation and window size was plotted on log-log scales, whereby the slope reflects the DFA exponent. To enhance the interpretation of the results, the

DFA exponents were converted into a commonly used fractal dimension (FD) scale based on the conversion formula provided by Wijnants and colleagues (Wijnants, Cox et al., 2012; Wijnants, Hasselman, Cox, Bosman, & Van Orden, 2012):

$$FD = .4\alpha^2 - 1.2\alpha + 2, \quad (1)$$

where α is the dfa exponent. A resulting FD close to 1.5 reflects white noise, close to 1.1 reflects brown noise, and close to 1.2 reflects pink noise (e.g., Van Orden et al., 2003).

For each rower we determined whether the observed FD fell outside the limits that we may expect in the case of a white noise pattern. Subsequently, we tested whether the temporal structures of the elite rowers (the rowers of Team B) were closer to pink noise than those of the sub-elite rowers (the rowers of Team A). For this test we used Monte Carlo Permutation, which has high statistical power for smaller sample sizes (e.g., Todman & Dugard, 2001; Van Geert, et al., 2012). To interpret the magnitude of the difference between the teams, Cohen's *d* (observed difference divided by the pooled SD) is reported.

3.3 Results

First, to ascertain the validity of our results, for each participant we checked whether the log-log relationship between window size and mean fluctuation approached a straight line in the selected data range, which was the case (r^2 varied between .97 and 1.00). Then, to determine whether the peak-to-peak interval variations deviated from white noise, we reshuffled the force-peak time-interval series 100 times for each participant (cf. Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995). This entails that the mean and standard deviation of the original interval series were kept the same, whereas the sequence of interval-data was randomized. Figure 4 shows that the FD's based on the reshuffled data were characterized by normal curves centered around the value of 1.5, which corresponds to white noise. For each participant the actual FD of the measured interval series fell outside the 95% confidence limits of the distribution in the direction of pink noise (i.e., a FD of 1.2).

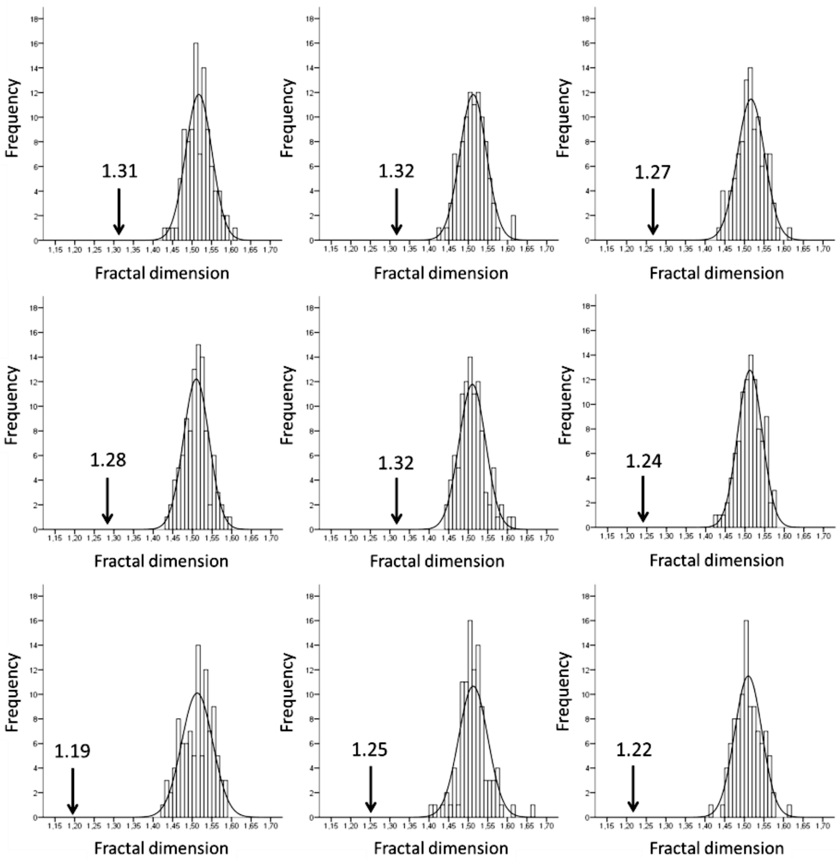


Figure 4. Fractal dimensions for each participant of Team A and Team B according to 100 reshufflings of the interval series data, and the actually observed values (indicated by black arrows).

Furthermore, we tested whether the mean FD of participants in Team B (elite rowing team) was significantly closer to pink noise (i.e., lower) than the FD of participants in Team A (sub-elite rowing team). Figure 5 shows that for each individual team member of Team B the FD was closer to pink noise than for each member of Team A. With the Monte Carlo permutation test we determined the probability that the observed difference between Team A and Team B could be caused by chance alone, by simulating that chance. This was done by repeatedly (10,000 times) redistributing the data to determine the probability of finding the same or a more extreme result. We found that the average FD of participants in Team A (M = 1.30, SD = .03) and of participants in Team B (M = 1.22, SD = .03) dificantly (p = .003, d = 3.06).

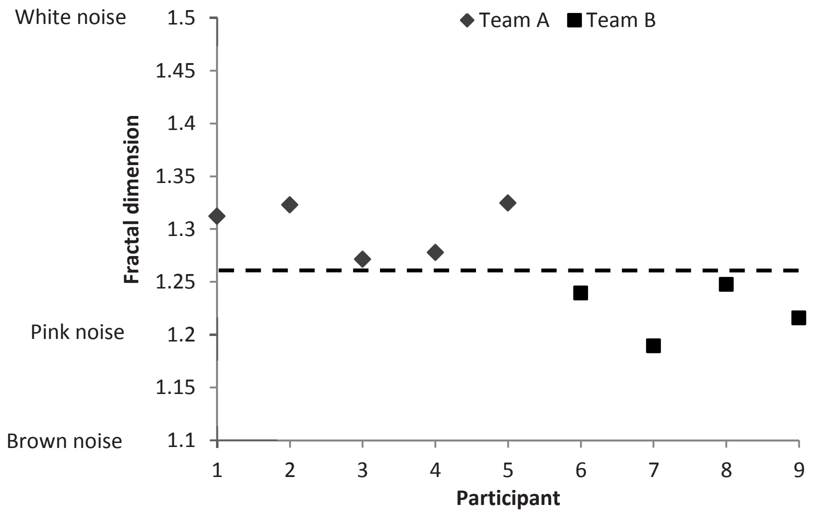


Figure 5. Fractal dimensions of participants in Team A and Team B. The dashed line separates the two teams.

3.4 Discussion

Variation is an essential feature of motor performance, and its structure is assumed to reveal information about the dynamic organization of the human motor system (e.g., Glass, 2001; Goldberger et al., 2002; Van Orden et al., 2003; Wijnants, 2014). By applying nonlinear time series analyses, we found an absence of a white noise (random) temporal structure in unconstrained rowing-ergometer performance (i.e., intervals between peak forces). Overall, this result is in line with recent findings on pacing of long-distance runners (Hoos et al., 2014) and power output variation of cyclists (Tucker et al., 2006). Considering the converging evidence that the current and previous findings provide,, it seems unlikely that sport performance is generated by independently operating component processes that perform specific (motor) functions in relative isolation.

In such a case, each rowing stroke would result from a process unrelated to that of the previous stroke, for example when a central pattern generator or motor program commands each new rowing stroke (cf. Goldberger et al., 2002; Wijnants, 2014).[3]

However, contrary to the previous studies in the domain of sports, which reported signatures of brown noise (Hoos et al., 2014; Tucker et al., 2006), we found prominent patterns of pink noise. In fact, none of our participants' force peak-to-peak interval series demonstrated a pattern close to brown noise. The differences between our research outcomes and those of Hoos et al. (2014) and Tucker et al. (2006) are in accordance with our earlier suggestion that additional (competition) constraints may result in a different organization of the motor system. More specifically, these differences support the notion that the competitive situation in the previous studies elicited a relatively rigid organization of the motor system. Indeed, the athletes in the studies of Hoos et al. (2014) and Tucker et al. (2006) probably exerted more conscious control over their performance, which was confirmed by the authors themselves. They stated that athletes in their studies generally followed a "fast-slow-fast" strategy (Hoos et al., 2014) and placed a significant increase in power output near the end of the trial (Tucker et al., 2006). This suggests that athletes made minor adaptations during short periods, nested in relatively large adaptations over the entire performance duration, which is (statistically) typically expressed in a brown noise pattern.

Our second major finding was that rowers from the elite rowing team had FDs closer to pink noise than rowers from the sub-elite team. This is in line with earlier outcomes in the domain of motor control, showing that effective behavior expresses more pink noise than less effective or unhealthy behavior (e.g., Glass, 2001; Goldberger et al., 2002), and that temporal structures of variation show more prominent patterns of pink noise when a task is well-mastered (Wijnants et al., 2009). Therefore, in line with Wijnants et al. (2009) we propose that the coordination among component processes involved in the generation of (relatively unconstrained) rowing strokes is more effective as skill level increases.

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[3] Although some researchers have proposed that sources of pink noise can be injected in particular local components such as central pattern generators (Torre & Wagenmakers, 2009), researchers have now reached consensus that pink noise does not arise from specific components within the system, but from complex interactions among the system components across different time scales (Delignières & Marmelat, 2013).

This is expressed in a more optimal mixture between rigidity and random variation, which may be a key characteristic of elite performance (cf. Davids et al., 2003; Phillips et al., 2012; Seifert et al., 2013).

Implications and Limitations

To date, assessments of sport and motor performance have mainly focused on some potential performance predictor *x* that may explain a significant portion of variance in performance outcome *y* (Atkinson & Nevill, 2001). Such assessments are the result of studies that (a) focus on sample means; (b) do not examine the performance process over time, but take snap-shot measures of the performance; and (c) treat variation as random (i.e., white noise). However, variation during (natural) sport performance can reveal information about the complexity of the human motor system and the effectiveness of an athlete's behavior, which should not be discarded. Our finding that the temporal structure of variation deviated from white noise for each rower, suggests that single-cause mechanisms or a linear causal chain of component processes are unlikely to account for the resulting rowing ergometer performance. Hence, applying the tools of complex systems science, nonlinear time series in particular, has great potential to advance insights into sport performance processes as they unfold in real-time (Kuznetsov et al., 2014).

One particularly interesting avenue for future research would be to examine how behavioral systems organize themselves under different circumstances. In this study force-peak interval series of rowers' (natural) stroke performance revealed prominent patterns of pink noise. We have suggested that temporal structures of variation in sport performance reveal signatures of brown noise when additional (competition) constraints are imposed. In addition, researchers have proposed that noise patterns may whiten when random perturbations are applied to an individual's motor behavior (e.g., Diniz et al., 2011; Wijnants et al., 2009; Wijnants, 2014).

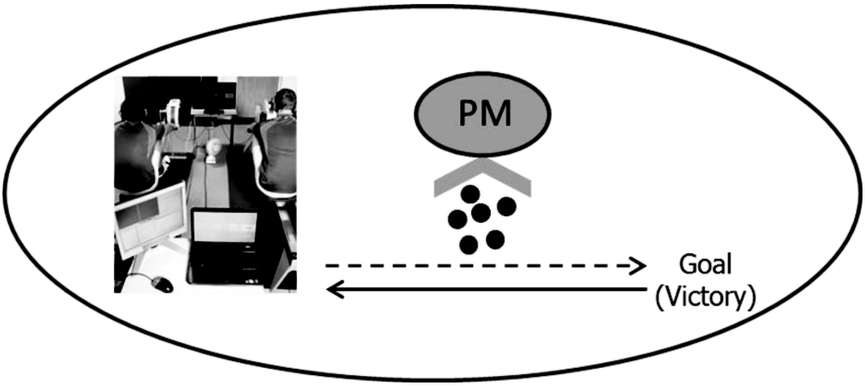
Furthermore, we found a clear relation between temporal structures of variation and rowing expertise-level. Therefore, in the future, researchers and practitioners should consider information on variation in rowing strokes (and sport performance in general) as a potentially important performance parameter that could be used for monitoring purposes. It might be, for instance, that the presence of more pink noise in time series of rower's natural (or preferred) rowing strokes is an indicator of the rower's ability to increase the stroke frequency to higher limits. This suggestion follows from findings of Torre (2010) in a study on bimanual tapping. She showed that the intensity of long-range correlations (i.e., pink noise) is significantly correlated with the movement frequency at which individuals shift their pattern of coordination (from anti-phase to in-phase). In other words, more pink noise was associated with the ability to persist in a particular coordination pattern at a high movement frequency.

However, some limitations should be pointed out with respect to the generalizability of the present findings. Although ergometer rowing is widely used as a mean to test rowers, and as a replacement for on-water practice, clear implications of the current study for actual on-water rowing cannot (yet) be provided. Furthermore, the sample size was rather small, and larger samples including a variety of skill levels could further enrich insights. In the current study we chose to focus on rowers from the same club who did not differ in terms of age and rowing experience, but who did differ in terms of their achievements in recent competitions. Although this resulted in a small sample size, we found significant and strong results, which provides promising prospects for a complexity perspective on sport and motor performance.

Conclusion

Here, we showed that temporal structures of rowers' force-peak intervals during ergometer rowing are not random, but are close to pink noise. Furthermore, we found that rowers of an elite team expressed even more prominent patterns of pink noise, which is the hallmark of well-coordinated and effective behavior (e.g., Goldberger et al., 2002; Van Orden et al., 2003; Wijnants et al., 2009; Wijnants, 2014). We propose that (skilled) rowers' performance of ergometer strokes naturally emerges from an ongoing dynamic interaction between various motor processes across multiple time scales, which is in accordance with the complex systems perspective in sports (Davids et al., 2003, 2014; Seifert et al., 2013). We believe that future applications of the complexity perspective will advance insights in the domain of sport and motor performance.

Chapter 4: How Psychological and Behavioral Team States Change During Positive and Negative Momentum



This chapter is based on:

Den Hartigh, R. J. R., Gernigon, C., Van Yperen, N. W., Marin, L., & Van Geert, P. L. C. (2014). How Psychological and Behavioral Team States Change during Positive and Negative Momentum. *PLoS ONE 9(5):* e97887. doi:10.1371/journal.pone.0097887

Abstract

In business and sports, teams often experience periods of positive and negative momentum while pursuing their goals. However, researchers have not yet been able to provide insights into *how* psychological and behavioral states actually change during positive and negative team momentum. In the current study we aimed to provide these insights by introducing an experimental dynamical research design. Rowing pairs had to compete against a virtual opponent on rowing ergometers, while a screen in front of the team broadcasted the ongoing race. The race was manipulated so that the team's rowing avatar gradually progressed (positive momentum) or regressed (negative momentum) in relation to the victory. The participants responded verbally to collective efficacy and task cohesion items appearing on the screen each minute. In addition, effort exertion and interpersonal coordination were continuously measured. Our results showed negative psychological changes (perceptions of collective efficacy and task cohesion) during negative team momentum, which were stronger than the positive changes during positive team momentum. Moreover, teams' exerted efforts rapidly decreased during negative momentum, whereas positive momentum accompanied a more variable and adaptive sequence of effort exertion. Finally, the interpersonal coordination was worse during negative momentum than during positive momentum. These results provide the first empirical insights into actual team momentum dynamics, and demonstrate how a dynamical research approach significantly contributes to current knowledge on psychological and behavioral processes during goal pursuit.

4.1 Introduction

During the 34th America's cup (September 2013), the American catamaran came backfrom a 1-8 disadvantage to 8-8. Then, in the winner-takes-all deciding race, Team USA started lagging behind Team New-Zealand, but turned the momentum and sailed to a historical victory. While in the ancient Greek times Homer suggested that momentum shifts are controlled by Gods' interference in human affairs (see Adler, 1981), current researchers acknowledge that positive momentum—progressing in relation to the goal—and negative momentum—regressing in relation to the goal—elicit psychological and behavioral changes, termed *psychological momentum* (PM) (Gernigon et al., 2010). Still, researchers have not yet been able to capture *how* psychological and behavioral states actually change when teams acquire positive or negative momentum. In the current study, we propose a paradigm advocated by complex dynamical systems theorists (e.g., Haken et al., 1985; Schöner & Kelso, 1988), allowing us to experimentally examine changes in psychological and behavioral performance variables during positive and negative momentum.

Earlier Research on Team Momentum

Periods of positive and negative momentum can be observed in various achievement contexts, such as presidential campaigns and business, but are probably most apparent in sports (Adler, 1981; Briki, Doron, Markman, Den Hartigh, & Gernigon, 2014; Markman & Guenther, 2007). Hence, most research on team momentum has been conducted in this domain. Quantitative studies conducted so far have increased insights into *which* psychological variables are higher as a result of positive momentum, compared to negative momentum or no momentum (Eisler & Spink, 1998; Miller & Weinberg, 1991; Stanimirovic & Hanrahan, 2004). For example, providing members of volleyball teams with questionnaires containing either a hypothetical positive momentum scenario (their team came back from behind) or a no-momentum scenario (the score kept close), researchers found that participants in the positive momentum scenario reported more momentum, confidence, and control, but also lower levels of anxiety and discouragement than participants in the no-momentum condition (Eisler & Spink, 1998; Miller & Weinberg, 1991). Moreover, effects of the positive momentum scenario were found to be stronger if the momentum occurred in a crucial phase of the competition (Miller & Weinberg, 1991) and if the team members felt highly cohesive (Eisler & Spink, 1998).

In an experimental study that took into account negative momentum as well, volleyball teams had to perform three competitive trials (Stanimirovic & Hanrahan, 2004). After each trial the experimenter indicated whether the team performed better (positive momentum condition) or worse (negative momentum condition) than the opponent team. The authors found that momentum perceptions, collective efficacy—team members' perceptions of their team's ability to successfully perform the task (Bandura, 1997)—and positive affect were higher in the positive momentum condition, whereas negative affect was higher in the negative momentum condition. In line with this, perceptions of momentum and collective efficacy generally increased over the three positive momentum trials, whereas negative affect decreased. In contrast, momentum perceptions, collective efficacy, and positive affect decreased over the negative momentum trials, whereas negative affect increased.

These previous studies showed that positive team momentum leads to various positive feelings and perceptions, and negative momentum to negative feelings and perceptions. However, it remains unknown *how* the psychological changes occur over the course of positive and negative momentum. Furthermore, it is unclear how momentum relates to performance change, because studies investigating the momentum-performance relationship have revealed mixed results. That is, researchers have suggested that performance improves with positive momentum (Miller & Weinberg, 1991), but several studies did not find this effect (Miller & Weinberg, 1991; Stanimirovic & Hanrahan, 2004; Taylor & Demick, 1994). Likewise, negative momentum is typically assumed to result in performance deterioration (Taylor & Demick, 1994), but has also been linked to performance improvement (Stanimirovic & Hanrahan, 2004). This positive effect of negative momentum has been explained in terms of a negative facilitation tendency (Cornelius, Silva, Conroy, & Peterson, 1997; Perreault, Vallerand, Montgomery, & Provencher, 1998), or in terms of reactance (see Briki, Den Hartigh, Hauw et al., 2012 in individual sports). According to both explanations, team members (or individual athletes) would increase their efforts in order to overcome their negative momentum.

Taken together, previous research has demonstrated that both psychological variables and performance are influenced by momentum (positive or negative), but it remains unknown *how* these variables change over time. This could be attributed to the primary focus on snapshot measures after manipulated or naturally occurring momentum periods during a fixed time (or scoring) span. That is, team momentum studies examined psychological variables and performance outcomes at only one point in time (for an exception, see Stanimirovic & Hanrahan, 2004; in this study measures were taken after three volleyball tasks, however, this does not allow for a true analysis of trajectories of psychological and performance changes). In the current study, we therefore conducted a process-oriented study aimed to provide the first insights into the nature of psychological and behavioral performance changes during positive and negative team momentum. These aims are in direct accordance with early (Adler, 1981) and recent (Gernigon et al., 2010) theoretical propositions stating that PM is a dynamical phenomenon.

The Dynamical Nature of Team PM

According to early theoretical assumptions, positive and negative (team) PM states can emerge and disappear, and their intensity may increase or decrease (Adler, 1981; Adler & Adler, 1978). Based on qualitative results in handball, researchers recently suggested that positive and negative team PM involve multiple psychological (e.g., emotions, feelings of confidence and cohesiveness) and behavioral (e.g., level of energy and activity) factors, that both undergo upward and downward changes over time (Moesch & Apitzsch, 2012). This suggestion supports the most recent theoretical definition of PM as “a positive or negative dynamics of cognitive, affective, motivational, physiological, and behavioral responses (and their couplings) to the perception of movement toward or away from either an appetitive or aversive outcome” (Gernigon et al., 2010, p. 397). Gernigon et al. (2010) proposed that PM can be conceived as a complex dynamical system.

Simply put, a complex dynamical system is a set of interconnected elements that undergoes change (Nowak & Vallacher, 1998). According to the dynamical systems perspective, the state of a system does not merely vary as a function of the value of one or a few independent variables, but also as a function of its preceding states (e.g., Van Geert, 1997; 2009a). That is, an event may change the state of a system (or not), depending on the history of the states of that system. Related to this, the change in the system's state can be nonlinear (e.g., Kelso, 1995; Nowak & Vallacher, 1998). For instance, when the system finds itself in a stable negative state—e.g., being desperate after some errors—, one or a few positive events such as experiences of success may not directly boost one's PM. On the other hand, when the stability of the system's negative state is low—e.g., making errors, but knowing your form is not bad—, one positive event can be sufficient to give rise to a positive PM experience (for more theoretical explanations of the dynamical systems approach in psychological and social sciences, see Kelso, 1995; Nowak & Vallacher, 1998; Thelen & Smith, 1994; Van Geert, 1994).

In individual sports, indications that PM can indeed be considered as a complex dynamical phenomenon have recently been found. In a qualitative study researchers found that positive and negative PM experiences involve a complex interplay between perceptions, emotions, cognitions, and behaviors (Briki, Den Hartigh, Hauw et al., 2012). Furthermore, in a recent experiment in which cyclists were competing, it was found that progressing in relation to the goal (i.e., victory) gives rise to a positive PM experience that develops relatively late, whereas a negative PM experience develops rapidly when regressing in relation to the goal (Briki et al., 2013).

Examining Team PM Dynamics

The conception of team PM as a dynamical phenomenon and the analogy between PM and complex dynamical systems, implies that the dynamical systems theory (DST)—"an approach to the description and explanation of change" (Van Geert, 2009a, p. 243)—should be used to study this topic. Because it is impossible to measure all variables related to changes in team PM (these are numerous, see Briki, Den Hartigh, Hauw et al., 2012; Moesch & Apitzsch, 2012), an important step in obtaining an understanding is to track the development of global level variables that can best describe team PM (i.e., collective variables, see Arrow, McGrath, & Berdahl, 2000; Nowak & Vallacher, 1998). Literature on team performance considers collective efficacy as a crucial global team variable, which is related to team momentum and may dynamically fluctuate over time. Indeed, an earlier study already found a general increase in collective efficacy in a positive momentum scenario and a decrease in a negative momentum scenario (Stanimirovic & Hanrahan, 2004), which is in line with the suggestion that teams can enter a positive and negative efficacy-momentum spiral during a competition (Bandura, 1997).

Another global psychological team variable is task cohesion, which is the degree to which team members work together to achieve a task or goal (Carron & Hausenblas, 1998). Task cohesion is considered a powerful team attribute highly related to performance (Carron, Brawley, & Widmeyer, 1998; Carron, Bray, & Eys, 2002). Moreover, it is considered a dynamical construct, which may vary from second to second during a competition (Buton, Fontayne, Heuzé, Bosselut, & Raimbault, 2007) and is related to team momentum (Adler, 1981; Eisler & Spink, 1998). Positive and negative dynamics in both team efficacy and task cohesion may thus reflect the development of team's positive and negative PM experiences.

The ongoing performance process during positive and negative team momentum has not yet been empirically studied. As discussed earlier, research has mainly focused on performance outcome measures of momentum (e.g., Miller & Weinberg, 1991; Stanimirovic & Hanrahan, 2004). However, the earliest theoretical work on momentum already suggested that the performance process in terms of effort exertion undergoes typical changes over the course of positive and negative momentum. More specifically, according to Adler's (1981) theory, the start of positive momentum can be characterized by momentum building, a phase in which efforts are high. Once momentum is established, a phase characterized by an economy of efforts or 'cruising' would be observed, during which a moderately strong level of exertion is sustained. With the goal within reach, effort exertion may naturally decrease, called coasting (see also Briki, Den Hartigh, Hauw et al., 2012). Then, as the goal to be reached is near, a re-momentum is common, during which more efforts are exerted than previously, as a kind of 'kick towards the finish'. Next to this dynamic development of effort exertion, the theory also states that positive momentum accompanies high coordination and rhythmicity of movements (Adler, 1981).

On the other hand, the performance tendency during negative momentum would generally be negative. However, at the start of the negative momentum period, a team may exert high efforts to overcome this (for a comparable tendency in individual momentum, see Briki, Den Hartigh, Hauw et al., 2012; Perreault et al., 1998), which carries the risk of an overabundance of efforts (Adler, 1981). Subsequently, voluntarily abandoning the activity is a common response when the negative momentum persists. When this is impossible (e.g., during a sports match), people may continue sinking until the end of the activity. Furthermore, movements would be more erratic during negative momentum (Adler, 1981).

Thus, based on the earlier literature on team momentum, we considered collective efficacy, task cohesion, exerted efforts, and interpersonal coordination as crucial performance, and team PM-related variables that may display specific dynamics during positive and negative momentum. To provide a first empirical examination of the team PM dynamics, we used a rigorous experimental dynamical systems method, originally intended to study how different coordination patterns form in biological systems (Haken et al., 1985; Schöner & Kelso, 1988). According to this method, a parameter (i.e., control parameter) should be scaled upwards and downwards to examine how the system moves to its different collective states. Given that positive and negative PM develop when progressing or regressing in relation to the goal, experimentally scaling a team's position (progress and regress) would allow a thorough examination of the psychological and behavioral team dynamics during positive and negative momentum. For the current study, team rowing was chosen as a research context, because team members are highly interdependent in this type of sport, both psychologically and behaviorally. In addition, objective measures of force exertion and interpersonal coordination could directly be obtained in an experimental setting (i.e., on rowing ergometers).

4.2 Method

Participants

To optimize the validity of our design and the resulting outcomes, we recruited a sample consisting of participants for whom reaching a goal during a rowing task would be meaningful. Hence, we contacted a board member of a rowing club to approach competitive rowers. Twenty-two Dutch rowers (18 male and 4 female) of four different rowing teams participated. Their mean age was 20.14 years (*SD* = 1.86), and on average the participants were active rowers at a rowing club for 1.14 years (*SD* = 1.02). All four teams practiced together several times a week for about five months. In the current study, eleven teams of two rowers were formed by pairing the participants randomly with one team member.

Experimental Design

The study took place in a room of the university, in which a research setup was built for this study (see Figure 6). The setup included two rowing ergometers (Concept 2, Model E, Inc., Morrisville, VT), a table with a monitor in front of the ergometers, a table with two computers behind the ergometers, Nintendo Wii remotes above the ergometers, and force sensors (MEAS, France) attached between the handles and the chains of the ergometers. On both ergometers we set the drag factor at 120 with PM4 performance monitors. This drag factor value corresponds to the resistance set by rowers for their workouts. While one of the computers behind the ergometers served to register the data from the Wii remotes and force sensors (see measures section), the other computer served to create the positive and negative momentum scenarios with race simulation software. This software enabled to program races involving (moving) avatars of two rowing boats that could be displayed on the screen in front of the ergometers. Furthermore, the software allowed entering items (i.e., questions the participants had to answer) at fixed intervals during the race.

Figure 6. Research setup.

Race Scenarios

To program credible race scenarios for our participants, we constructed the races in consultation with (inter)national rowers and rowing coaches, and we pilot tested some scenarios with four rowers and four other athletes in eight sessions. When rowing against an opponent of comparable level, a time-gap of 8 seconds was perceived as considerable, but manageable, while more than 8 seconds would become unrealistic to overcome. The maximum duration of a strenuous rowing exercise turned out to be between 10 and 13 minutes. Taking this information into account, we programmed momentum scenarios that followed the experimental guidelines as set by earlier researchers (Haken et al., 1985), and included three phases: A priming phase, a momentum phase, and a completion phase (see Figure 7).

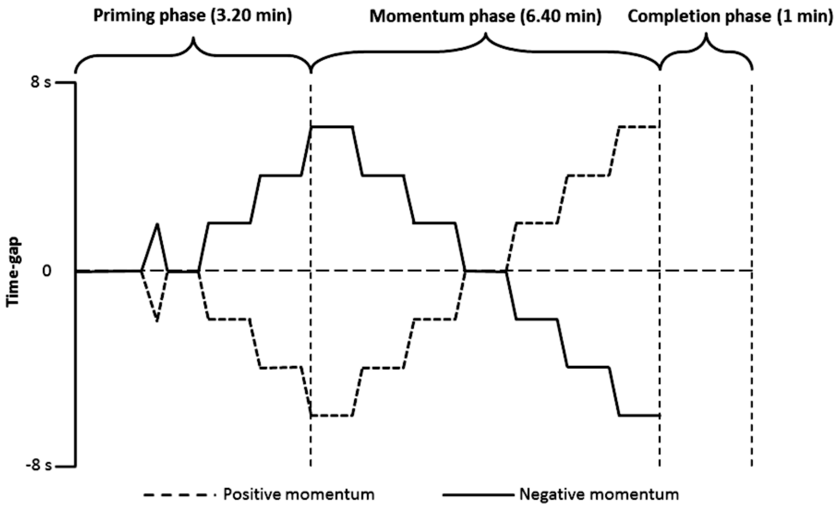


Figure 7. Illustration of the constructed positive and negative momentum scenarios.

The priming phase covered the first 3.20 min. During the start of this phase, the avatars kept in step and one of the avatars took a short lead to add credibility to the scenario. Then, the avatar of the participants either moved to a lag of 6 seconds, or to a lead of 6 seconds, which was the starting point for the positive or negative momentum phase, respectively. During the momentum phase that followed, the team's boat gained 2 seconds each minute until they led by 6 seconds (positive momentum), or lost 2 seconds each minute until they lagged behind by 6 seconds (negative momentum). This phase lasted 6.40 minutes. During the completion phase, which lasted 1 minute, the final time-gap between the avatars was reached, which was between a 6-second lag and a 6-second lead. This phase was not included in the data analyses, but was added to avoid participants thinking that they were involved in identical race scenarios (although they were kindly requested not to discuss their race with other participants). However, none of the races ended in a (full) victory or defeat for the participating teams (i.e., winning or losing by 8 seconds).

Procedure

The study protocol was approved by the Ethical Committee of the Department of Psychology, University of Groningen. Each team (pair) participated in two sessions—one positive momentum session and one negative momentum session—in random order, spread over one to two weeks. Upon their arrival for their first session, the participants signed an informed consent form and a physical health form. Subsequently, we gave the participants a quick tour through the experiment room, during which we showed how we were able to capture their exerted efforts and coordination, and explained that we could connect their real-time performance to racing software. This tour served to avoid suspicion about possible manipulations during the study, and preceded the participants' warm-up activities. After the warm-up, we explained to the participants that they would be connected to the racing software. We told them that the race would be displayed on the screen in front of them, and we provided them with a clear goal: To beat the opponent by taking an 8-second lead. We added that if the race would become too long, it would be stopped to avoid too much exhaustion (note that in reality the race was already programmed at 11 minutes with no ultimate winner, and that the elapsed time was not displayed).

We explained to the participants that they would see two rowing boats on the race screen, a green and an orange boat. The green boat represented the participants' boat, whose speed would be based on a combination of their shared effort exertion and their coordination, as continuously collected by the racing software. We said that the speed of the other boat was based on the performance of another team at a comparable level, whose data had already been collected and uploaded into the software. Furthermore, we told the participants that the screen changed regularly to display two questions, and that the race screen would be shown again when both participants had verbally answered the questions. To avoid participants being able to hear each other and be influenced by each other's item answers during the race, we gave them soundproofed headsets. The participants' answers were recorded by voice recorders attached to their t-shirts.

When the participants were ready, a research assistant counted down and the race, along with the data collection from the force sensors and the Nintendo Wii remotes, were started. While they were rowing, the participants followed the (manipulated) development of the race on the screen. After the second session, we asked the participants to fill out a questionnaire including a manipulation check. All participants indicated a period corresponding to the actually manipulated momentum phases in their answers to the questions: “Was there a period you were moving toward the victory?”, “Was there a period you were moving toward the defeat?”, and “if yes, when was this period?”.

Measures of Psychological Variables

To minimize the possible interfering influence of answering questions during the race, we only picked one collective efficacy item and one task cohesion item, which could be verbally answered on a 9-point scale while rowing. The items appeared on the race screen 15 s after each change in time gap between the avatars (i.e., each minute). Collective efficacy items generally include team members’ confidence in their team’s abilities to produce specific attainments (e.g., bounce back from performing poorly) (Bandura, 2006; Feltz & Lirgg, 1998). Often, one general measure of collective efficacy is included in questionnaires as well, which reflects the team members’ confidence in the team’s abilities to win the competition, or outperform the other team (e.g., Feltz & Lirgg, 1998; Stanimirovic & Hanrahan, 2004). Therefore, we included such an item in the software, namely “Now, at this moment I am confident in our abilities to win this race” (1 = *not at all confident*, 9 = *very confident*).

A widely used cohesion questionnaire in achievement contexts, and in sport in particular, is the Group Environment Questionnaire (GEQ). We picked the item with the highest loading on the (group integration) task cohesion dimension found in a validation study of the questionnaire (Heuzé & Fontayne, 2002). The original item is “The members of my team are united in their efforts to reach the performance goals”, which we adapted to our research context by formulating the item as “Now, at this moment we are united in our efforts to win this race” (1 = *strongly disagree*, 9 = *strongly agree*).

Measures of Performance Variables

Pre-calibrated force sensors were attached between the handles and the chains of the ergometers to provide continuous data of effort exertion. The two force sensors were connected to a data acquisition card (DAQ), made by National Instruments (NI USB-6009). The DAQ served to transfer the data of the two force sensors to the computer via USB. A Matlab script was written to save the data in Volts (V) at a frequency of 100 Hz.

Nintendo Wii remotes, attached to the ceiling above the ergometers, contain infrared (IR) camera sensors (PixArt Imaging, Inc., Santa Clara, CA). The camera sensors tracked a light, which we placed on the handlebar of each ergometer, and which (also) emitted infrared light. This system provides accessible, high resolution and high-speed movement tracking (Lee, 2008). The temporal accuracy of the IR camera sensors was 100 Hz. We determined the spatial accuracy of the sensors by putting a light (the same as those placed on the handles) on a big rotating record turntable, placed at the same height as the handlebar. As the light continuously visited the same coordinates during each rotation, the Nintendo Wii IR camera sensors measured each coordinate within an error margin of 0 to 2 millimeters. Given the length of a rowing stroke—about 150 centimeters—we considered a spatial accuracy of 2 millimeters to be acceptable.

During the experiment, an application written in C allowed us to collect the (changing) positions of the lights in pixels (pix) via Bluetooth, while simultaneously collecting the exerted effort data.

Analyses

Before analyzing the data, the responses to the psychological items collected with the voice recorders were (double) checked by research assistants and entered in Microsoft Excel. The mean scores of the two members of each team were used for the analyses. The data in V from the force sensors were transformed to Newton units (N) according to a linear transformation provided by the manufacturer of the sensors. The mean force exertions per team in N were then taken into account for the analyses.

The positions of the handle bars as tracked by the Wii remote IR cameras in pix were transformed to centimeters (cm). Subsequently, we used a low-pass Butterworth filter in Matlab on the two time series of the positions, with a cut-off frequency of 4 Hz. We standardized the time series signals, and with the following formula we calculated the continuous relative phase (φ) via a Hilbert transformation (Pikovski, Rosenblum, & Kurths, 2003) to obtain accurate quantifications of the interpersonal coordination between the participants:

$$\theta_1(t) - \theta_2(t) = \arctan \frac{s_{H1}(t)s_2(t) - s_1(t)s_{H2}(t)}{s_1(t)s_2(t) + s_{H1}(t)s_{H2}(t)}, \qquad (2)$$

where $\theta_1(t)$ and $\theta_2(t)$ are the phases of each separate signal; $s_1(t)$ and $s_2(t)$ correspond to the real signals; and $H_1(t)$ and $H_2(t)$ correspond to the Hilbert transformations of $s_1(t)$ and $s_2(t)$.

We then applied Monte Carlo permutation tests for the actual analyses. The Monte Carlo test determines the probability that an observed outcome is caused by chance alone, by simulating that chance (e.g., Todman & Dugard, 2001; Van Geert et al., 2012). This is based on a repeated redistribution (e.g., 5,000 times) of the collected data, to determine the possibility that a similar or more extreme result can be found by chance. A great advantage of this technique is that the test statistics are based on the observed data distribution, rather than on a presumed (normal) distribution. Therefore, this procedure often has better explanatory value than conventional statistical techniques in the field of behavioral and social sciences, such as ANOVAs, particularly in the case of smaller sample sizes and skewed data distributions (Van Geert et al., 2012). In addition, the Monte Carlo technique is well suited to answer research questions that are difficult, or impossible to answer with conventional statistical techniques. One example is the calculation of a combined *p*-value, which we conducted for the mean relative phase and its standard deviation, in order to determine the quality of the coordination (see below).

Before running the Monte Carlo procedure, we divided the time series of the mean force exertion, the relative phase in degrees (φ), and the standard deviation of the relative phase (*SD*φ) into seven sections, corresponding to the seven periods in which there was a specific time-gap between the avatars on the screen, and to the number of psychological measures. Subsequently, we ran the Monte Carlo procedure, for which we shuffled the data of the different variables within the teams (pairs), rather than over the entire sample. The reason for this was that different teams could not be considered as one homogeneous sample (Arrow et al., 2000; McGrath, Arrow, & Berdahl, 2000). This choice thus enabled us to find regularities in the team dynamics, despite the heterogeneity of the teams (e.g., some teams had more power than other teams, which could obscure the presence of dynamical trends in exerted efforts shared between teams). With the Monte Carlo procedure, the observed outcome was compared to the outcome of the redistributed data after each round of shuffling. In this way, we tested 1) the overall change in the variables during positive and negative momentum separately, 2) differences between the overall changes in the positive and negative momentum scenarios, 3) time-gap to time-gap differences in mean exerted force during positive and negative momentum, and 4) differences between the scenarios in terms of collective efficacy, task cohesion, and a combination of the mean relative phase (φ) and its standard deviation (*SD*φ). A low probability (*p*-value) that the randomly redistributed data generate the same, or more extreme, results than those actually observed indicates that the observed results are unlikely to be caused by chance alone. Finally, with regard to the average differences between the scenarios on the variables collective efficacy and task cohesion, we divided the averages by the standard deviations for each team. In order to provide a conservative effect size, we determined the average effect size (*ES*) based on the individual team results.

4.3 Results

Our results are based on the positive and negative momentum sessions of eight male teams (for an overview of the sample means and standard deviations of the psychological and behavioral variables, see Table 4). One member of a female team mistakenly believed that, during the first session, her team was the orange boat, despite the instruction that they were the green boat. Furthermore, one female team and one male team literally gave up rowing during their first (negative) momentum session. The data of these three teams could therefore not be included in the analyses of the dynamics over both the positive and negative momentum session. Results of the psychological and behavioral dynamics will be reported separately.

Table 4. Overview of sample results (means and standard deviations) for collective efficacy, task cohesion, exerted efforts, and relative phase, according to momentum scenario and time-gap in seconds.

	Collective efficacy		**Task cohesion**		**Exerted efforts (N)**		**Relative phase (°)**	
Scenario:	*Positive*	*Negative*	*Positive*	*Negative*	*Positive*	*Negative*	*Positive*	*Negative*
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Time-gap								
All	6.29 (1.22)	5.20 (1.79)	6.87 (1.38)	6.10 (1.57)	146.33 (8.82)	144.53 (10.20)	4.86 (3.49)	5.48 (3.79)
-6	4.44 (.56)	3.13 (1.16)	6.38 (1.75)	4.88 (1.66)	156.21 (9.79)	138.71 (8.72)	3.37 (3.28)	4.26 (2.63)
-4	5.63 (.74)	3.69 (.84)	6.25 (1.31)	4.88 (1.46)	147.20 (7.90)	139.68 (7.00)	4.58 (4.53)	5.70 (3.50)
-2	6.13 (.58)	4.38 (.99)	6.69 (1.19)	5.69 (1.19)	145.51 (8.19)	141.22 (6.75)	4.93 (4.30)	6.79 (4.40)
0	6.31 (.70)	5.25 (.93)	6.63 (1.53)	6.00 (1.31)	143.06 (8.69)	141.77 (8.19)	5.79 (3.01)	5.94 (4.63)
+2	6.75 (.85)	5.63 (.64)	7.06 (1.12)	6.56 (1.08)	144.20 (6.15)	143.91 (7.86)	4.21 (3.41)	5.67 (3.79)
+4	7.25 (.71)	6.38 (.92)	7.38 (1.36)	6.81 (1.00)	142.26 (7.39)	148.93 (8.19)	5.82 (3.29)	5.30 (4.45)
+6	7.56 (1.05)	7.94 (1.15)	7.69 (1.22)	7.88 (1.06)	145.85 (8.25)	157.48 (12.24)	5.30 (3.04)	4.71 (3.72)

Note. Exerted efforts are expressed in Newton units (N), and relative phase measures in degrees (°).

Psychological Dynamics

Figure 8A shows the dynamics of collective efficacy. Monte Carlo tests revealed that this variable significantly increased during positive momentum (M_{change} = 3.13, SD = .92, p < .001), and decreased during negative momentum (M_{change} = -4.81, SD = 1.58, p < .001). The decrease during negative momentum was significantly steeper than the increase during positive momentum (M_{diff} = 1.69, p < .01). In addition, collective efficacy was higher during positive momentum (M = 6.29, SD = .63) than during negative momentum (M = 5.20, SD = .60, p < .001, ES = .67). Significant differences (p < .05) between the scenarios were found at time gap values from -6 s until +2 s.

The dynamics of task cohesion are displayed in Figure 8B. This variable increased significantly during positive momentum (M_{change} = 1.31, SD = .70, p < .001), and decreased significantly during negative momentum (M_{change} = 3.00, SD = 1.56, p < .001). The decrease during negative momentum was significantly steeper than the increase during positive momentum (M_{diff} = 1.69, p < .01). Moreover, task cohesion was generally higher during positive momentum (M = 6.87, SD = 1.28) than during negative momentum (M = 6.10, SD = 1.09, p < .001, ES = .75), and local differences were found at time gap -6 s and -4 s (p < .05).

Behavioral Dynamics

Figure 9A displays the dynamics of exerted efforts. Based on the Monte Carlo tests we found that exerted efforts significantly decreased during positive momentum (M_{change} = -10.36, SD = 8.38, p < .001) as well as negative momentum (M_{change} = -18.78, SD = 11.13, p < .001). Overall, the decrease was steeper during negative momentum than during positive momentum (M_{diff} = 8.41, p < .01). Accordingly, exerted efforts did not differ between scenarios at the start of the momentum periods—i.e., at +6 s in the negative momentum scenario and -6 in the positive momentum scenario—, whereas force exertion was significantly higher at the end of the positive momentum scenario—i.e., at +6 s—than at the end of the negative momentum scenario—i.e., -6 s—(p < .05).

Looking at the dynamics within the scenarios, pairwise comparisons between successive time gaps in the positive momentum scenario showed that effort exertion significantly *de*creased from time gap -6 s to -4 s and from time gap +2 s to +4 s ($p < .05$). A significant *in*crease in efforts was found from time gap +4 s to +6 s ($p < .05$). During negative momentum, significant *de*creases were found from time gap +6 s to +4 s and from +4 s to + 2 s ($p < .05$).

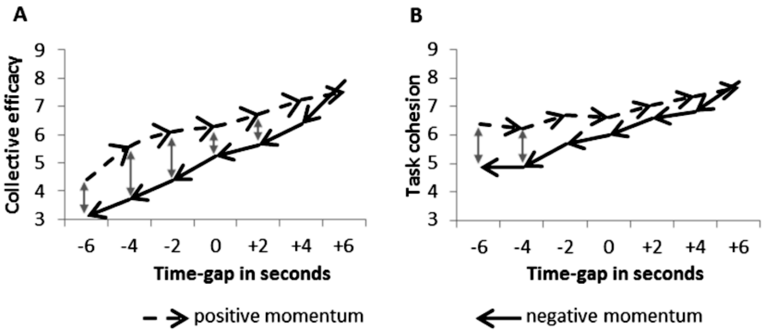


Figure 8. Dynamical trends of collective efficacy (A) and task cohesion (B) during positive and negative momentum. Grey double arrows indicate at which time-gaps there is a significant difference ($p < .05$) between the positive and negative momentum scenario.

The dynamics of the relative phase (φ) and its standard deviation (*SD*φ) are shown in Figure 9B. Overall, the combination of the mean continuous relative phase (φ) and its stability (*SD*φ) was better (i.e., closer to 0) over the course of positive momentum ($\varphi = 3.49$, $SD\varphi = 7.43$) than during negative momentum ($\varphi = 3.79$, $SD\varphi = 7.79$, $p_{\text{combined}} < .05$). However, no significant differences were found between the scenarios at same values of time gaps. Within the scenarios separately, we found a decreasing trend in *SD*φ during positive momentum, which significantly differed from the slight increasing trend during negative momentum ($M_{\text{diff}} = 1.35$, $p < .05$). Regarding the mean relative phase (φ), we found no significant increasing or decreasing trends during either positive or negative momentum.

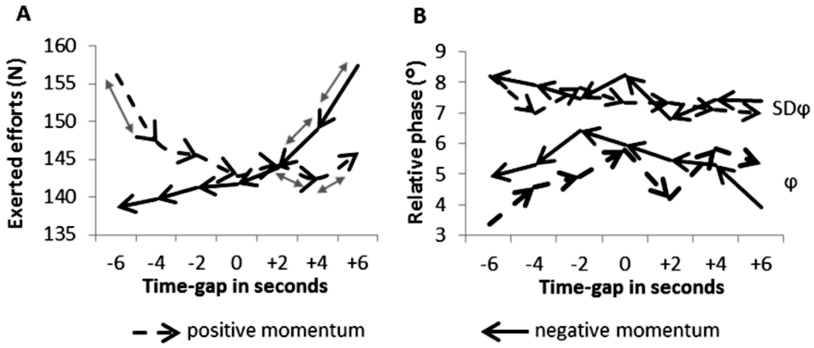


Figure 9. Dynamical trends of exerted efforts (A) and interpersonal coordination (B) during positive and negative momentum. Exerted efforts are expressed in Newton (N). The grey double arrows in Graph A indicate significant changes ($p < .05$) from time-gap to time-gap. The mean relative phase and its standard deviation (Graph B) are expressed in degrees.

4.4 Discussion

Previous empirical research has demonstrated that psychological states and performance are often influenced by positive and negative team momentum (Eisler & Spink, 1998; Miller & Weinberg, 1991; Stanimirovic & Hanrahan, 2004). Insights into the nature of psychological and behavioral performance changes during positive and negative team momentum are still lacking, however. To provide such insights, we used the dynamical systems approach to examine psychological (collective efficacy and task cohesion) and behavioral (exerted efforts and interpersonal coordination) changes by experimentally varying the position in relation to the team goal of winning the race (cf. Haken et al., 1985). This approach is in concordance with theoretical propositions stating that PM is a dynamical phenomenon (Gernigon et al., 2010), which, as we will discuss below, is supported by our data on the psychological and behavioral dynamics.

Psychological Dynamics

With regard to collective efficacy, we found an increase during positive momentum and a decrease during negative momentum, which supports the theoretical assumption that teams may enter a positive or negative efficacy-momentum spiral during performance (Bandura, 1997). In addition, these results are in line with the earlier finding that team members' collective efficacy increased and decreased when they experienced repeated success and failure, respectively (Stanimirovic & Hanrahan, 2004).

A similar fluctuating pattern was observed for task cohesion: An increase was present during positive momentum and a decrease during negative momentum. In an earlier study, it was already found that task cohesion is related to team PM (Eisler & Spink, 1998). However, in that study the authors treated task cohesion as a "static" team attribute influencing the extent to which teams are sensitive to positive momentum periods, whereas the current study shows that task cohesion is also actually involved in the PM process. We therefore propose that task cohesion is a dynamical, fluctuating variable (Buton et al., 2007) that undergoes positive and negative changes during positive and negative momentum. All in all these results of collective efficacy and task cohesion suggest that the upward and downward dynamics of these variables characterize the psychological experience of positive and negative team PM, respectively.

Interestingly, the nature of the changes in collective efficacy and task cohesion was different depending on whether momentum was positive or negative. More specifically, decreases in collective efficacy and task cohesion during negative momentum were steeper than the increases during positive momentum. This asymmetry could not be detected in earlier snapshot studies on team momentum (e.g., Eisler & Spink, 1998; Miller & Weinberg, 1991), and was therefore not anticipated. Yet, the asymmetry supports the general assumption that negative events have a bigger psychological impact than equivalent positive events (Baumeister, Bratslavski, Finkenauer, & Vohs, 2001; Kahneman & Tversky, 1979). Moreover, it is in line with results from individual sports, showing that negative PM was triggered more easily than positive PM (Briki et al., 2013). Related to this asymmetry, collective efficacy and task cohesion were generally higher in the positive momentum scenario than in the negative momentum scenario. Given that the scenarios were exactly symmetrical, this finding suggests that team PM experiences are not only dependent on the static situation within the competition, but also on the history of progress or regress (cf. Briki, Den Hartigh, Markman, & Gernigon, 2014; Briki et al., 2013; Gernigon et al., 2010). This thus suggests that team PM is history dependent—a typical dynamical property—, which supports the proposition that PM could be considered a complex dynamical system (Gernigon et al., 2010).

It is noteworthy that the history of progress or regress particularly played a role when being behind (i.e., at negative values of time gap). This means that having gained the lead at the start of the race—the start of the negative momentum scenario—accompanied approximately the same levels of collective efficacy and task cohesion, as having gained the lead after being behind—end of the positive momentum scenario. On the other hand, lagging behind after having had the lead—end of the negative momentum scenario—accompanied lower collective efficacy and task cohesion than lagging behind at the start of the race—start of the positive momentum scenario. This suggests that in particular losing while having been close to the goal (i.e., winning) has a disproportionally strong psychological impact compared to losing while one has never been close to the goal. This finding is in accordance with the well-known phenomenon that perceiving an outcome as nearly (but ultimately not) occurring has powerful psychological consequences, because almost attaining the desired outcome makes the counterfactual outcome (e.g., I could have won) more salient (Kahneman & Tversky, 1982; Markman, Elizaga, Ratcliff, & McMullen, 2007; Medvec & Savitsky, 1997; Medvec, Madey, & Gilovich, 1995).

Behavioral Dynamics

The dynamics of the behavioral performance variable effort exertion were not characterized by straightforward upward or downward trends during positive and negative momentum. Strikingly, exerted efforts followed a pattern that has been proposed by Adler's (1981) early social theory of momentum. In the positive momentum session we found high exerted efforts at the start, which corresponds to a 'building momentum' phase according to Adler (1981). Subsequently, when winning two seconds efforts decreased and moved to a relatively stable exertion, which corresponds to a 'cruising' phase. Then a short significant drop in efforts occurred, which is in line with a coasting tendency, a tendency that has also been found in research on individual PM (Briki, Den Hartigh, Hauw et al., 2012). Finally, effort exertion increased, which is in line with the 'final kick' phase, reflecting a last boost in efforts when perceiving that the goal is near (Adler, 1981).

Negative momentum involved a steeper overall decrease in exerted efforts than positive momentum. Moreover, the effort exertion decreased over the entire negative momentum phase, which corresponds to a sinking tendency according to Adler's (1981) momentum theory. The decrease in exerted efforts was rapid between time gap values of +6 s and +2 s, which could be interpreted as an early dropping tendency because of losing hope in a positive outcome (see also Briki et al., 2013). Noteworthy, two teams in our original sample showed an even more striking dropping tendency, these teams literally gave up when perceiving the opponent was coming back. This latter tendency supports the idea that people sometimes voluntarily drop the activity when they reach a point at which they become certain that they will fail (Adler, 1981).

This study's second performance variable was interpersonal coordination. Again in line with Adler's (1981) theory of momentum, we found that the quality of interpersonal coordination was higher during positive momentum than during negative momentum. Moreover, the stability of the coordination (relative phase) improved during positive momentum. We did, however, not find clear patterns with regard to the mean relative phase over the course of positive and negative momentum. The absence of such patterns could be explained by the robust finding that people automatically coordinate their movements over time when they are performing a comparable rhythmical task (Coey, Varlet, Schmidt, & Richardson, 2011; Issartel, Marin, & Cadopi, 2007; Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Richardson, Marsh, & Schmidt, 2005; Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998; Schmidt, Carello, & Turvey, 1990; Schmidt & O'Brien, 1998). This continuous synchronization tendency could have been further strengthened by the fact that our sample consisted of rowing teams that were trained to stay coordinated.

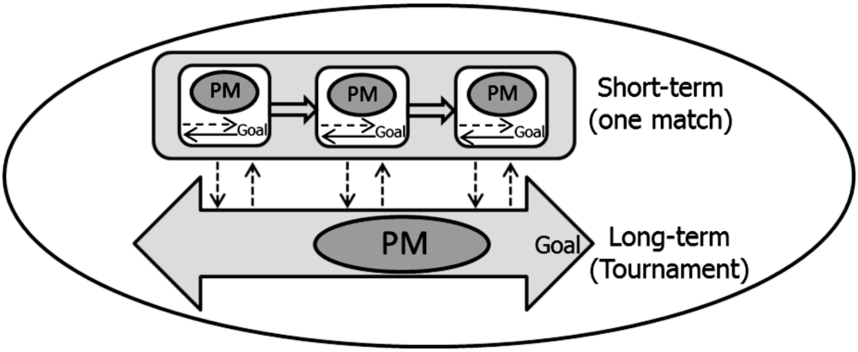
Conclusions and Future Directions

In conclusion, in the current chapter we introduced a complex dynamical approach to study the team PM process. We showed that, relative to positive team momentum, negative momentum elicits stronger (opposite) psychological changes and accompanies different (less adaptive) behavioral regulation. The asymmetry between positive and negative psychological team momentum dynamics, depending on the history of progress and regress, points to the relevance of pursuing a dynamical approach. Within the domain of social sciences—and team dynamics in particular—patterns of change often remain unnoticed, because optimal standardization and ruling out the role of history are common practice in mainstream experimental designs (Arrow et al., 2000). In addition, the results of exerted efforts and interpersonal coordination brought insights into the actual performance dynamics during positive and negative momentum. The lack of consistent results with regard to the momentum – performance outcome relationship in earlier research might be explained by our findings that performance processes are non-stationary during positive and negative momentum. Indeed, if we would have taken single snapshots of exerted force at some time-gap value in the positive or negative momentum session, for instance, we could have observed values reflecting relatively high, medium, and low performance.

Our results provide the first quantitative insights into the dynamical process of team PM. One may object that the sample size on which our insights are based is rather small. However, when studying processes, small samples can be very valuable provided that the cases (i.e., participants) are well-chosen (Van Geert, 2011). In the current study, we selected competitive rowers for whom reaching a goal during an ergometer competition was meaningful. This selection was necessary to ensure that progressing and regressing in relation to that goal would elicit a positive and negative PM experience. Obviously, giving priority to a high quality sample often has consequences for the quantity of the sample.

Another point that should be noted is that the dynamical experimental method we applied is often used to find classical dynamical patterns in terms, stability and metastability (see Haken et al., 1985; Issartel et al., 2007; Schmidt et al., 1990, 1998; Schöner & Kelso, 1988), which we did not primarily focus on. Rather, we described and interpreted our results in terms of asymmetric and history-dependent patterns which, according to us, can be considered interesting dynamics underlying human psychological and behavioral functioning. Indeed, while the “classical” dynamical patterns are often found in physics and motor control, human psychological and behavioral systems could often be characterized by various dynamical trajectories (Van Geert, 1994). Related to this, we may conclude that future researchers who aim to study psychological and behavioral processes would benefit from an approach that is specifically focused on describing and explaining change. A complex dynamical systems design as we applied (but also model simulations and dynamical research in natural situations, see Arrow et al., 2000; McGrath et al., 2000) could greatly aid in getting a better grip on the dynamical nature of social and performance-related phenomena such as team psychological momentum.

Chapter 5: Psychological Momentum Within and Across Task Performance: Evidence for Interconnected Time Scales



This chapter is based on:

Den Hartigh, R. J. R., Van Geert, P. L. C., Van Yperen, N. W., Cox, R. F. A., & Gernigon, C. (2015). Psychological momentum within and across task performance: Evidence for interconnected time scales. Manuscript submitted for publication.

Abstract

Psychological momentum (PM) is a well-known experience in sports and other achievement settings, and may develop on the long-term (across a series of tasks), as well as on the short-term (during one particular task). Applying a complex dynamical systems perspective, the current study provides the first experimental attempt to test whether PM processes across these two time scales are interconnected. In this experiment, competitive athletes were striving to win a prize during a rowing-ergometer tournament (long-term), consisting of multiple races (short-term). In the positive momentum condition, the participants won the first two races, whereas in the negative momentum condition, they lost the first two races. In the third race, all participants took a lead at the start, after which they gradually moved toward a defeat. The results show that in the positive momentum condition, the participants had increasing long-term perceptions of momentum and self-efficacy, whereas these long-term perceptions decreased in the negative momentum condition. Furthermore, relative to the negative momentum condition, in the positive momentum condition participants' short-term perceptions of momentum, self-efficacy, and exerted efforts were higher in the third race, and their perceptions of momentum and self-efficacy decreased less rapidly. Theoretically, the interconnection between long- and short-term PM provides evidence that PM is a dynamical phenomenon spanning multiple time scales. From a practical perspective, managers, teachers, and coaches should be aware that their subordinates, students, or athletes are likely to carry their performance history into the next task.

5.1 Introduction

Periods of momentum are reported in various performance contexts, such as presidential campaigns, business, and sports in particular (e.g., Adler, 1981; Iso-Ahola & Dotson, 2014; Markman & Guenther, 2007). The term *psychological momentum* (PM) refers to the psychological and behavioral changes that occur when actors perceive that they are progressing (positive momentum) or regressing (negative momentum) in relation to their goal (Adler, 1981; Gernigon et al., 2010; Markman & Guenther, 2007; Vallerand et al., 1988). Previous studies, mostly using written or audiovisual scenarios in a sports context, found that psychological states are more positive for athletes who progress in relation to their goal (i.e., the victory) than those who regress or keep up with their opponent (Briki, Doron, et al., 2014; Eisler & Spink, 1998; Markman & Guenther, 2007; Miller & Weinberg, 1991; Vallerand et al., 1988). In line with these findings, research in which an actual sport task had to be performed (i.e., a cycling contest) demonstrated that participants who came from behind to tie their opponent had more positive psychological perceptions, in terms of optimism, confidence, energy, and control, than participants who kept up with their opponent throughout. In addition, the participants who came back from behind exerted more efforts, i.e., pedaled faster (Perreault et al., 1998). Thus previous literature has shown that progression or regression affects PM, both at the psychological and behavioral level (for a review on PM across performance domains, see Iso-Ahola & Dotson, 2014).

The above mentioned findings on PM are in line with the general literature on goal striving, in particular with regard to the role of ‘discrepancy’, ‘acceleration’ and ‘quasi-acceleration’ in relation to a desired goal (e.g., Carver & Scheier, 1990, 1998; Higgins, 1987; Hsee, Salovey, & Abelson, 1994). According to these authors, positive and negative affect are caused by high or low goal discrepancies (Higgins, 1987), and changes in affect are determined by changes in velocity (i.e., acceleration or deceleration) in relation to the desired goal (Carver & Scheier, 1990, 1998; Hsee et al., 1994). A principal difference between these goal striving theories and PM is that, already since its first conceptualization, PM has been described as a *dynamical process* embracing both psychological and behavioral changes, which may emerge and disappear during task performance (Adler, 1981; Adler & Adler, 1978), and entails typical properties of complex dynamical systems

(Gernigon et al., 2010)[4]. Simply put, a complex dynamical system is a set of interconnected components that undergoes change, and is characterized by some defining properties such as *emergence* of self-sustaining patterns (attractors), *non-linear transitions* between attractors, *history-dependence*, and *interconnected time scales* (Kelso, 1995; Nowak & Vallacher, 1998; Thelen & Smith, 1994; Van Geert, 1994).

Previous studies have provided evidence for some of these dynamical properties of PM, looking at nonlinearity and history-dependence in particular (see next section). However, the defining property of *interconnected time scales* has never been empirically examined, and studying this may provide deeper insights into the complex dynamic nature of PM. Approaching PM as a complex dynamical system entails that this interconnection should be detected. That is, we should find that single performances (e.g., one sport match) influence the long-term PM development (e.g., during a tournament), which in turn influence the short-term PM dynamics in the next performance. To provide novel insights into PM dynamics, we designed an experiment to examine the development of long- and short-term PM, and the interconnection of these two time scales.

Dynamical System Properties of Psychological Momentum

Indications for the *emergence* of PM out of the interactions between multiple components can be derived from qualitative studies, showing that several personal, environmental, and social factors in interaction shape a PM experience (e.g., Briki, Den Hartigh, Hauw et al., 2012; Jones & Harwood, 2008; Moesch & Apitzsch, 2012; Taylor & Demick, 1994). Furthermore, experimental studies have found evidence of *nonlinear transitions* between positive and negative PM that are *history-dependent*. That is, during sport performance a change in PM depends on the history of successive PM states as shaped by the continuous course of events (Briki et al., 2013; Den Hartigh, Gernigon, Van Yperen, Marin, & Van Geert, 2014; Gernigon et al., 2010). In one study, Briki et al. (2013) examined cyclists who competed with each other on home trainer bicycles in a (manipulated) race. One competitor started moving toward the defeat, but then gradually progressed

[4] Note that Carver and Scheier also attempted to merge their goal striving theory with the theory of complex dynamical systems (Carver & Scheier, 2002). However, empirical demonstrations of this proposition are lacking.

toward the victory (positive momentum scenario), whereas the opponent underwent the exact opposite (negative momentum scenario). Briki et al. (2013) found an asymmetrical pattern: The positive change in PM perceptions in the positive momentum scenario was delayed, whereas there was a rapid negative change in PM perceptions in the negative momentum scenario. These results imply that transitions between positive and negative PM are nonlinear, and that a relatively long history of progressing in relation to the victory seems to be needed to enter positive PM, whereas a short history of regressing already triggers negative PM. At the behavioral level, the authors found that exerted efforts decreased quite rapidly when regressing in relation to the victory. Taken together, Briki et al.'s (2013) findings imply that negative PM is a stronger attractor than positive PM, that is, negative PM is entered more rapidly and is harder to escape (see also Den Hartigh et al., 2014; Gernigon et al., 2010).

Interconnected Time Scales

One defining property of dynamical systems that has not been studied in relation to PM is the interconnection of time scales. Theoretically, this property entails that processes associated with faster changes in the system influence processes that govern slower changes of the system, and vice versa (e.g., Newell et al., 2001; Wijnants, Cox et al., 2012). More specifically, it would imply that short-term (e.g., daily) events shape the psychological and/or behavioral processes that develop on the long term, which in turn feed into the dynamical processes on the short term (e.g., Granic & Patterson, 2006; Newell et al., 2001; Thelen & Smith, 1994; Van Geert, 2009b).

To date, theoretical and empirical demonstrations of the interconnection between time scales (unrelated to PM) are primarily found in the domain of learning (e.g., Newell et al., 2001; Steenbeek et al., 2012; Van der Steen et al., 2014; Zanone & Kelso, 1992). For instance, single learning sessions in a teaching context have been found to shape a child's learning development across successive sessions, which in turn shapes the learning dynamics within (next) sessions (Steenbeek et al., 2012; Van der Steen et al., 2014). For instance, Steenbeek et al. (2012) found that a suboptimal session between a teacher and a child (short-term) influences the (problematic) learning trajectory across sessions (long-term), which in turn influences the dynamics between the teacher and child in the next session (short-term), and so forth. In the domain of motor learning, Newell et al. (2001) described how single motor-learning events change the movement repertoire of an individual so that, after some interim-period, new movement solutions are available during a next motor-learning event. The theoretical explanation for these findings would be that repeated events (e.g., performances) change what is called the *attractor landscape*, that is, the *range* of stable patterns to which the system may converge (e.g., Granic & Patterson, 2006; Newell et al., 2001; Thelen & Smith, 1994; Zanone & Kelso, 1992).

Given that the development of PM is inherently related to the goal in relation to which an actor progresses or regresses (e.g., Adler, 1981; Gernigon et al., 2010; Markman & Guenther, 2007; Vallerand et al., 1988), the time scale should be defined at the level of the goal that is pursued. This goal can be a typical short-term goal (within a task, such as winning a match) or a longer-term goal (across multiple tasks, such as winning a tournament) (Adler, 1981). Hence, long- and short-term PM would develop when progressing or regressing in relation to the goals at the respective time scales. In accordance with the analogy between PM and complex dynamical systems, we expected that these time scales would be interconnected, as expressed in a mutual influence between long- and short-term PM processes.

The Current Study

In order to explore the interconnection between long- and short-term PM, we examined (a) whether single performances influence the development of individuals' long-term PM, and (b) whether the individuals' long-term PM feeds into their short-term PM dynamics. Given that PM embraces a wide range of psychological and behavioral features (Briki, Den Hartigh, Hauw et al., 2012; Gernigon et al., 2010), we identified the essential variables describing the PM dynamics. First, at the psychological level, PM was reflected by the direct perception of momentum (i.e., of progress in relation to the goal), which is an emergent perception during goal striving (e.g., Briki et al., 2013; Briki, Den Hartigh et al., 2014; Carver & Scheier, 2002). Second, we focused on another emergent variable during goal striving that is assumed to be related to momentum: Self-efficacy (confidence in one's abilities to reach a goal; Bandura, 1997; Shaw, Dzewaltowski, & McElroy, 1992). Both these psychological variables were thus examined in relation to individuals' long- and short-term goals. At the behavioral level we focused on exerted efforts, which have been found to undergo typical changes during positive and negative PM on the short-term, that is, during task performance (Briki et al., 2013; Den Hartigh et al., 2014; Perreault et al., 1998). Hence, changes in perceived momentum, self-efficacy (long- and short-term) and exerted efforts (short-term) can provide qualitative insights into PM dynamics.

Accordingly, we designed an experiment in which meaningful long- and short-term goals could be defined, repeated psychological measures could be collected within and across tasks, and objective measures of effort exertion could be collected during task performance. More specifically, individuals pursued a long-term goal (winning a prize) in a rowing-ergometer tournament, consisting of multiple races in which the individuals were striving for a short-term goal (winning the race). Our first hypothesis was that races that end in winning or losing would lead to the development of positive or negative long-term PM, respectively. This would provide evidence for an influence of the short-term time scale (single task-performances) on the long-term time scale (long-term tournament PM) (cf. Granic & Patterson, 2006; Newell et al., 2001; Van Geert, 2009b).

Furthermore, with regard to short-term PM dynamics, one of the most evident findings is that negative PM develops relatively rapidly, suggesting that negative PM is a strong attractor (Briki et al., 2013; Den Hartigh et al., 2014; Gernigon et al., 2010). However, recall that the theory of dynamical systems implies that successive real-time events or performances change an individual's attractor landscape (e.g., Granic & Patterson, 2006; Newell et al., 2001; Zanone & Kelso, 1992). Accordingly, our second hypothesis was that repeated successful or unsuccessful races would affect the PM attractor landscape, so that individuals enter negative PM less rapidly *within* a race after previous successes (i.e., when having developed long-term positive PM), compared to athletes with a history of failure (i.e., who have developed long-term negative PM). In other words, the short-term negative PM attractor would be weaker for athletes who have developed long-term positive PM. If both hypotheses are confirmed, this would provide empirical support for an interconnection between short- and long-term PM processes, and thereby deeper insights into the dynamics of PM.

5.2 Method

Participants

We approached male competitive athletes from different sports clubs, and asked whether they would be willing to participate in a rowing-ergometer tournament in which they could win money. Twenty-five athletes consented to participate, who were active in the following sports: Squash (*n* = 3), basketball (*n* = 1), swimming (n = 6), hockey (*n* = 5), speed skating (*n* = 1), floorball (*n* = 3), soccer (*n* = 3), and tennis (*n* = 3). The mean age of the participants was 24.05 years (*SD* = 2.26), and on average the participants practiced 4.72 times a week (*SD* = 4.39).

Experimental Setup and Procedure

The protocol of the study was approved by the ethical review board of the Department of Psychology, University of Groningen. The research setup included two rowing ergometers that were placed next to each other (see Figure 10). A force sensor was attached between the handle and the chain of each ergometer, and a curtain was placed in between the two ergometers to prevent the participants being able to see each other during the races. An HD screen was placed on a table in front of the ergometers, serving to broadcast the ongoing race as well as the psychological items that were displayed at repeated intervals during the races. Behind the ergometers was a table with two computers: One computer served to register the data from the force sensor, the other was connected to the HD screen and contained the software used to program the races and display the psychological items.

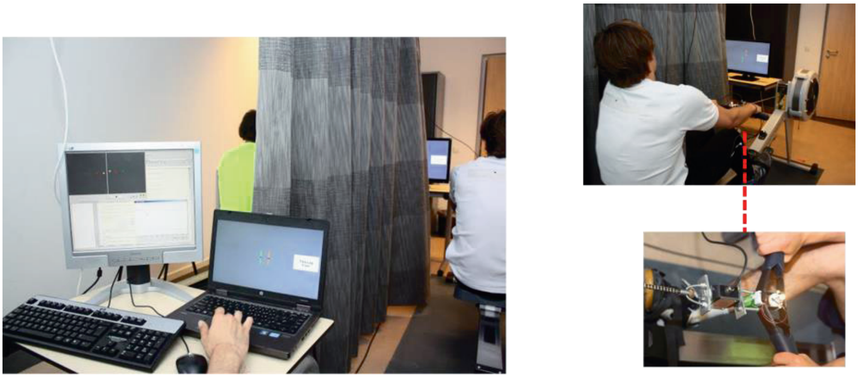


Figure 10. Research setup.

The participants were successively involved in four ergometer trials, at intervals of about one session each week. The first trial was a baseline session, which served to obtain information about the participants' demographics and ergometer performance. Subsequently, participants were assigned to a positive momentum or negative momentum condition, and completed one race in the second and one race in the third trial, which they either won (positive momentum condition) or lost (negative momentum condition). Finally, in the fourth trial, the participants in the positive momentum *and* the negative momentum condition were involved in a race that was programmed so that all participants gradually moved from a lead to a defeat (see Table 5). After the fourth trial, the participants were debriefed.

Table 5. Race configurations (8 minutes each) in the positive and negative momentum conditions.

Condition	Competition	Points at start	Race configuration per minute							
Positive Momentum	1	0	0	-3	0	+3	0	+3	+6	+9
Negative Momentum	1	0	0	+3	0	-3	0	-3	-6	-9

Condition	Competition	Points at start	Race configuration per minute							
Positive Momentum	2	+1	0	0	+3	0	-3 / 0	+3	+6	+9
Negative Momentum	2	-1	0	0	-3	0	+3 / 0	-3	-6	-9

Condition	Competition	Points at start	Race configuration per minute							
Positive Momentum	3	+2	0	+3	+6	+3	0	-3	-6	-9
Negative Momentum	3	-2	0	+3	+6	+3	0	-3	-6	-9

First Trial

The first trial was a baseline session that we conducted with each participant individually. Upon his arrival in the experiment room for the first time, the participant signed an informed consent form, a physical health form, and filled out his demographic information. Then, we gave the participant a tour through the experiment room, we demonstrated the devices that enabled us to collect detailed information about his performance (e.g., force sensor), and we explained that we could connect the two ergometers to organize races. Subsequently, the participant did a warm-up on the ergometer for 5 minutes, after which he did a 1-minute, maximum-effort test. During this test we collected the participant's exerted efforts with the force sensor, as well as the distance he rowed according to the performance monitor (PM 4) of the ergometer.

Based on the baseline information, we grouped the participants according to rowing performance and height. This procedure served to organize credible races between competitors of comparable level and posture. In addition, to avoid a priori expectations about the outcome of the race, participants who were from the same sports club were not scheduled to compete with each other, and none of the participants competed against the same opponent twice. The participants were randomly assigned to the positive momentum or negative momentum condition (see Table 5). Finally, three individuals (two regular exercisers and one rower) were added to provide sufficient flexibility in the tournament schedule. These individuals were used to fill in possible gaps in the schedule and were available to replace possible drop-outs.

Second and Third Trial

The second and third trials were two races in which participants directly competed with each other (head-to-head). When participants arrived for their race, they were introduced to each other, and did their warm-up activities. Then, the experimenter gave the instructions. He reminded the participants that they were involved in an ergometer tournament, which had been developed with our unique equipment. We told the participants that they would compete in a maximum of five races. Their goal was to win 3 points, which would mean they would obtain a money prize (we told them that we had 300 euros to distribute over the winners). Winning the first, second or third race resulted in 1 point each, whereas 1 point would be subtracted when losing. We also told them that 2 points could be won or lost in the fourth and fifth race (i.e., in total 4 points could be won or lost in these races). Note that in reality there was no fourth and fifth race, but that we provided this information so that participants in the positive *and* negative momentum group would, in theory, both be able to reach the long-term goal in the third race (i.e., the fourth and last trial). Thus, the only difference between the conditions was that, before the fourth trial, participants in the positive momentum condition had progressed in relation to the long-term goal of winning 3 points and the money prize (having collected +2 points), whereas the participants in the negative condition had regressed (having -2 points).

We informed the participants that they would win the race by taking a 9-second lead on the opponent. Thus, the short-term goal was winning by taking this lead. We told the participants that their performance, which we continuously monitored, was projected on the moving avatars on the screen (a green and an orange rowing boat), so that they could follow the race. In reality, however, the scenarios of the races were programmed beforehand. The first and second race started with a five-minute period in which the competitors alternated leads of 3 seconds. Then, between the 5th and 8th minute, one of the competitors gradually progressed toward the victory (i.e., a 9-second lead) in steps of 3 seconds per minute, whereas the other moved to the defeat (see Table 5). Before the start of each race, we assigned an avatar to each participant by showing a green or orange paper, corresponding to the color of the participant's avatar on the screen (using a colored paper to inform the participant about the color of his avatar was particularly important for the fourth trial, see next sub-section). Depending on the condition the participant was in, his avatar either won or lost the first and second race (i.e., the second and third trial).

Furthermore, the experimenter informed the participants that the screen would regularly change to display two questions, and that the race would be displayed again after both participants had answered the questions aloud. To register the item answers, we attached voice recorders to the participants' t-shirts. Moreover, to avoid participants being able to hear each other and be influenced by each other's item answers during the race, they wore soundproofed headsets.

Once the participants were ready, the experimenter counted down and launched the race, along with the data collection by the force sensor. Finally, to assess long-term PM (whether the experience of the first race carried over to the end of the first interim-period), we gave participants a questionnaire before the second race (i.e., third trial).

Fourth Trial and Debriefing

The fourth trial was the last (third) race. Upon their arrival, participants filled out the long-term PM questionnaire again, in order to test the influence of the earlier race(s) on the long-term PM development (see *hypothesis 1*). Subsequently, we gave the instructions. Contrary to the previous two races, in the third race we showed a green paper to both participants before the start (note that the participants did not see the color that was shown to the opponent, because of the curtain that separated them). Doing this, we thus indicated to both participants that their performance was projected on the green avatar (neither of the participants was the orange avatar).

The scenario of the third race followed the methodological guidelines of Haken et al. (1985), who stipulated that changes in the behavior of a dynamical system (PM in this case) should be studied under the gradual variation of a control parameter that may lead the system to another state. More specifically, during the race, the participant's avatar first moved to a lead of 6 seconds, after which it gradually moved to a defeat—a lag of 9 seconds—in steps of 3 seconds per minute. Hence, the position in the race (relative to the victory) was our control parameter, whose gradual variation may elicit a change from positive PM to negative PM. The scenario of the third race thus allowed us to test whether participants in the positive momentum condition would enter negative PM less rapidly than the participants in the negative momentum condition (see *hypothesis 2*).

Directly after the third race, we gave participants a questionnaire including manipulation checks. After this questionnaire, we fully debriefed the participants about the manipulation of the races and the purpose of the study. None of the participants suspected that the races were manipulated. Finally, because participants could not actually win money as they thought, we rewarded them with 20 euros for their participation.

Measures of Long-Term Psychological Momentum

Questionnaires were used to assess participants' PM experiences with regard to the long-term (tournament) goal. One item was a direct measure of the perception of momentum, which was adapted from Vallerand et al. (1988): *At* *this moment I am progressing towards winning 3 points and the money prize*. This item could be answered from -3 (Not at all) to +3 (Very much). The second item was a self-efficacy measure, which we formulated according to Bandura's guidelines that self-efficacy items should represent an actor's perceived abilities to attain given accomplishments that pertain to the situational context (Bandura, 2006). Our self-efficacy item was: *At this moment, I am confident in my abilities to win 3 points and the money prize*, which could be answered from -3 (Not at all confident) to +3 (very confident). Based on the outcomes of our pilot study with competitive athletes, more items related to the perception of momentum and self-efficacy were not included, because this could make the participants suspicious (i.e., think they were being psychologically manipulated). In addition, note that the response scales were not the same as the ones traditionally used for momentum and self-efficacy items. The reason for choosing scales ranging from -3 to +3 was to stay consistent with the scales used during the races, and to obtain reliable responses throughout the study (see next sub-section).

Measures of Short-Term Psychological Momentum

The questionnaire items were adapted so that they pertained to the short-term goal of the race. The items were: *Now, at this moment… I'm progressing towards the victory* (perception of momentum; -3 = Not at all, +3 = Very much), and *Now, at this moment, I am confident in my abilities to win this race* (self-efficacy; -3 = Not at all confident, +3 = Very confident). These questions appeared each minute during the race (i.e., 15 seconds after each change in time-gap between the avatars). The choices for only two items and a response scale from -3 to +3, solved the issue that the experiment would be too cognitively demanding and that we would obtain less reliable item answers. In the pilot studies, athletes had difficulties providing accurate responses when being exposed to more than two questions and to response scales ranging from 1 to 7 or 9.

Exerted efforts were registered with the force sensors that were attached between the handles and chains of the ergometers. We collected the data in units of volts in Matlab, at a frequency of 100 Hz. Subsequently, we transformed the data to Newton units according to a linear transformation (see also Chapter 4). Given the continuous nature of the force-sensor measures, we divided the data into five sections before the analysis, corresponding to the periods in which there was a specific time-gap between the avatars on the screen. Hence, as for the perceptions of momentum and self-efficacy, we had one measure of efforts for each time-gap between the avatars. Moreover, to allow reliable comparisons, each participant's effort exertion was calculated relative to his average output during the 1-minute maximum-effort test in the baseline session.

Analysis

To examine the influence of single performances on individuals' long-term PM development (*hypothesis 1*), and how this feeds into the short-term PM dynamics in the third race (*hypothesis 2*), we used Monte Carlo permutation tests. The Monte Carlo test determines the probability that the observed result is caused by chance alone, by simulating that chance. This is based on a repeated shuffling of the collected data (i.e., 10,000 times across participants or time gaps, depending on the type of question), and a calculation of the probability that the same, or more extreme, result can be found by chance. Relative to traditional parametric (e.g., ANOVA) and nonparametric tests (e.g., Kruskal-Wallis), Monte Carlo tests are more appropriate in the case of relatively small sample sizes and/or skewed data distributions, and are highly suited to study patterns of change (Todman & Dugard, 2001; Van Geert et al., 2012). Furthermore, to provide a measure for the magnitude of our results, we calculated Cohen's *d*.

5.3 Results

Preliminary Analyses

Of the 25 competitive athletes, three were not taken into account for the analysis. One participant incurred a (soccer) injury before the fourth trial (i.e., third race). Another participant could not finish the fourth trial; his race was suspended because his opponent stopped rowing before the end of the race (this opponent was a regular exerciser who was added to the sample). Finally, one participant did not provide item-responses reflecting his momentum and self-efficacy perceptions during the fourth trial. Of the remaining 22 participants that finished the study, 11 were in the positive momentum condition and 11 in the negative momentum condition. We first tested whether participants in the two conditions differed on variables that may influence our results: Age, height, hours of practice per week, number of meters in the baseline session, and exerted efforts in the 1-minute maximal-test. No significant differences were found on any of these variables (*ps* > .05).

Long-Term Psychological Momentum

To determine the influence of single performances on the long-term PM development, we first compared the participants in the positive and negative momentum conditions at their levels of perceived momentum and self-efficacy before race 2 (i.e., after a victory or defeat in the first race) and before race 3 (i.e., after two victories or defeats). The results are displayed in Figure 11. Monte Carlo permutation tests revealed that the momentum perception before race 2 was higher for participants in the positive momentum condition (M = .64, SD = .50) than for those in the negative momentum condition (M = -.73, SD = .90; p < .001, d = 1.86). Before the third race, the momentum perception was also higher in the positive momentum condition (M = 1.18, SD = .75) than in the negative condition (M = -1.91, SD = .94; p < .001, d = 3.62). With regard to self-efficacy, measured before race 2, the participants in the positive momentum condition scored higher (M = .45, SD = .82) than those in the negative momentum condition (M = -.45, SD = 1.21; p = .03, d = .88). Before the third race, participants' self-efficacy was also higher in the positive momentum condition (M = 1.18, SD = .75) than in the negative condition (M = -1.55, SD = 1.13; p < .001, d = 2.85).

Furthermore, we tested whether perceived (long-term) momentum and self-efficacy increased and decreased for participants within the positive and negative momentum condition, respectively. The increase in the perception of momentum approached significance for the participants in the positive momentum condition (p = .06, d = .85), whereas the momentum perception significantly decreased for those in the negative momentum condition (p = .007, d = 1.28). Furthermore, participants' self-efficacy significantly increased in the positive momentum condition (p = .04, d = .92) and significantly decreased in the negative momentum condition (p = .03, d = .93). Taken together, these results support our first hypothesis that races that end in winning or losing lead to the development of positive or negative long-term PM, respectively.

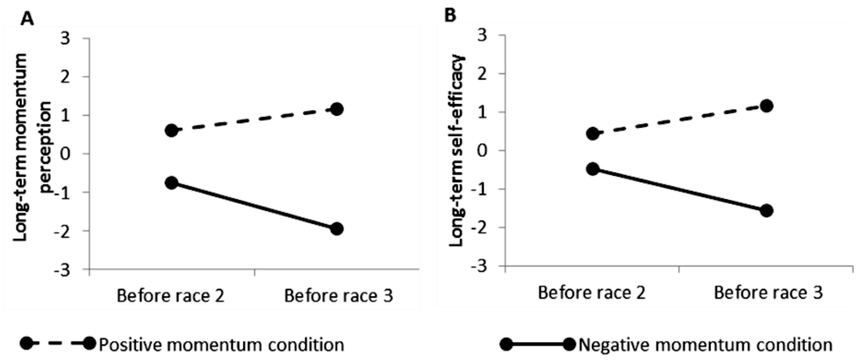


Figure 11. Long-term results of momentum perception (A) and self-efficacy (B) for the positive momentum condition and the negative momentum condition.

Short-Term Psychological Momentum

The short-term PM dynamics were examined in the third race when the participants were regressing from a lead of 6 seconds—close to victory—to a lag of 6 seconds—close to defeat. The changes in perceived momentum, self-efficacy, and exerted efforts are displayed in Figure 12. To examine whether the negative PM attractor was weaker for participants who developed long-term positive PM (see *hypothesis 2*), we first compared the participants in the positive and negative momentum conditions on the average values. Results showed that participants in the positive momentum condition had higher momentum perceptions (M = .45, SD = .69) than those in the negative momentum condition (M = -.65, SD = .65; p < .001, d = 1.66). Furthermore, self-efficacy was higher in the positive momentum condition (M = .31, SD = .65) than in the negative momentum condition (M = -.58, SD = .53; p < .001, d = 1.50). Finally, the relative efforts were higher in the positive momentum condition (M = 71.87%, SD = 4.51) than in the negative momentum condition (M = 67.73%, SD = 6.69, p = .05, d = .73).

Second, we tested differences between participants in the positive and negative momentum conditions in terms of the rate of decrease in perceived momentum, self-efficacy, and exerted efforts. We found that the decrease was significantly less steep (i.e., less rapid) in the positive momentum condition than in the negative momentum condition with regard to the perception of momentum (M_{diff} = 1.73; p < .001, d = 2.11) and self-efficacy (M_{diff} = 1.55; p < .001, d = 1.65). The decrease in efforts was not significantly less steep for the participants in the positive momentum condition (p = .12). Together, these results support our second hypothesis that the negative PM attractor is weaker for athletes who have developed long-term positive PM, compared to those who have developed long-term negative PM.

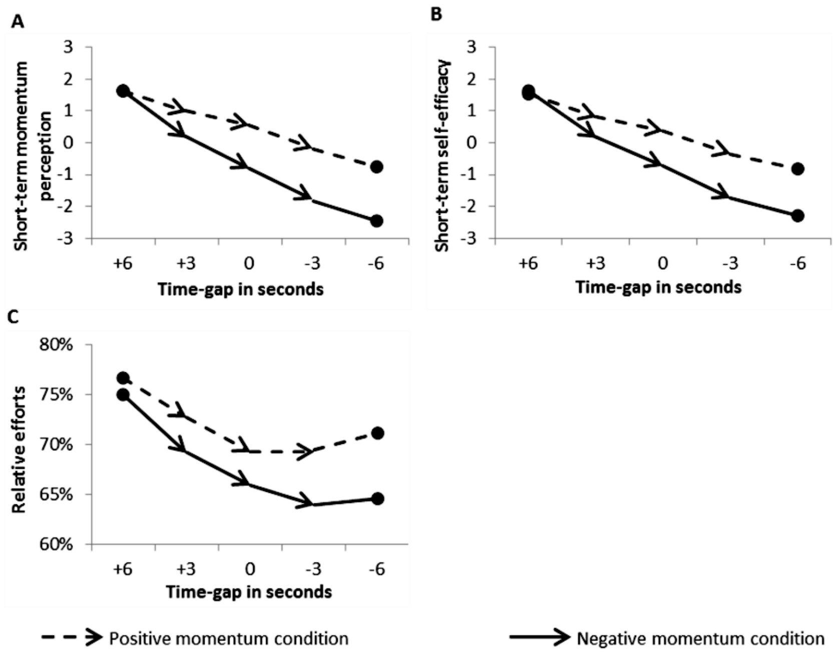


Figure 12. Short-term results of momentum perception (A), self-efficacy (B), and exerted efforts (C), according to time-gap and experimental condition.

5.4 Discussion

Recently, researchers have drawn a parallel between PM and complex dynamical systems, and have found that PM may develop nonlinearly, depending on the ongoing history of events (Briki et al., 2013; Briki, Den Hartigh et al., 2014;

Den Hartigh et al., 2014; Gernigon et al., 2010). More specifically, recent studies showed that, within a single sport contest, a state of negative PM develops rapidly, whereas positive PM develops after a relatively long history of positive events (e.g., winning seconds on the opponent). This suggests that negative PM is a stronger attractor than positive PM (Briki et al., 2013; Den Hartigh et al., 2014; Gernigon et al., 2010). Although the dynamical approach has improved the understanding of the PM process, one defining dynamical property has remained unexamined: Interconnected time scales (i.e., the connection between the long- and short-term PM process).

To fill this void, we first examined whether single performances affect athletes' long-term PM experiences. Compared to participants in the negative momentum condition who successively lost races, the participants in the positive momentum condition had higher perceptions of momentum and self-efficacy, before both the second and third race (i.e., after having won the first and second race). This finding is in line with the suggestion that PM may develop across successive tasks (Adler, 1981). We also found increases and decreases in perceptions of momentum and self-efficacy in the positive and negative momentum condition, respectively, although the increase in momentum perception approached significance in the positive momentum condition. This suggests that negative PM is not only triggered more easily during a task (Briki et al., 2013; Den Hartigh et al., 2014; Gernigon et al., 2010), but also across a series of tasks. Taken together, these results provide empirical support for our first hypothesis that single races that end in winning or losing lead to the development of positive or negative long-term PM, respectively.

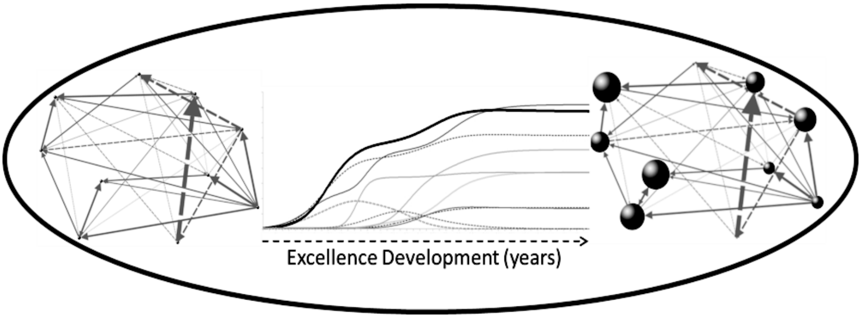
Secondly, we examined whether the long term PM that athletes developed over the course of multiple races feeds into the athletes' short-term PM (i.e., the psychological and behavioral dynamics within the subsequent (third) race). We found that perceptions of momentum and self-efficacy, as well as exerted efforts, were higher when participants had developed long term positive PM than when they had developed long-term negative PM. Moreover, perceptions of momentum and self-efficacy changed (decreased) less rapidly when participants had a history of successful races. The finding that participants who developed long-term positive PM were less sensitive to the gradual regression within the race, suggests that the previous successful or unsuccessful races affected the PM attractor landscape (cf. Granic & Patterson, 2006; Newell et al., 2001; Thelen & Smith, 1994; Zanone & Kelso, 1992). Our results thus imply that, in this case, the negative PM attractor had become weaker following successful races, which supports our second hypothesis.

In line with propositions to apply a complex dynamical systems perspective to the study of PM (Gernigon et al., 2010), the observed connection between short- and long-term PM suggests that PM is a dynamical phenomenon spanning multiple interconnected time scales. A limitation may be that our sample size was relatively small, which was due to the labor-intensive nature of the study and to the tournament schedule. To account for this, we used statistical analyses that are highly suited to dealing with smaller sample sizes (i.e. Monte Carlo tests). The credibility of our results is further strengthened by the large effect sizes we found (according to Cohen's (1988) guidelines, a *d* higher than .8 can be considered large). Another limitation may be that our study did not involve a control group that neither won nor lost the first two races. Because of the size of our sample, and for an optimal comparison, we decided to make two experimental groups that were exposed to exactly opposite scenarios in the first two races, and to the exact same scenario in the last race.

To conclude, this experiment provides the first demonstration of a connection between long-term and short-term PM. Short term (single task) performances shape individuals' long-term PM, which in turn constrain the PM dynamics within the next task. Because individuals pursue long-term goals, as well as short-term goals in virtually any achievement domain (e.g., sports, business, education), more insights could be gained when examining psychological and behavioral processes across, and within, task performances in natural situations (e.g., during a business project, or actual sport tournaments, cf. Minbashian & Luppino, 2014). Furthermore, it is worthwhile to explore whether the interconnection of time scales extends towards even longer-term processes (e.g., successive projects or a sports season). Finally, from an applied perspective, managers, teachers, and coaches should be aware that their subordinates, students, or athletes are likely to carry their performance history into the next task (see also Markman & Guenther, 2007). Although this carry-over effect could be advantageous when building positive PM, long-term negative PM seems to affect the short-term (within-competition) psychological and performance processes in a negative way.

Therefore, it may pay off to provide subordinates, students, or athletes with strategies to ‘bounce back’ after unsuccessful task performance (e.g., Galli & Vealy, 2008; Margolis & Stoltz, 2010; Tugade & Frederickson, 2004). For example, managers or coaches may offer a resilience training in order to improve the ability to overcome (successive) setbacks (Galli & Gonzalez, in press; for a specific outline of an existing resilience training program in the US army, see Reivich, Seligman, & McBride, 2011).

Chapter 6: Excellent Performance Likely Emerges Out of Dynamic Network Structures



This chapter is an adapted version of:

Van Geert, P. L. C., Den Hartigh, R. J. R., Steenbeek, H. W., & Van Dijk, M. W. G. (2014). *The* development of excellent human performance: A dynamic network model. Manuscript submitted for publication.

Abstract

For over a century, there exists an ongoing debate about the mechanism(s) explaining the development of excellent human performance. In the current chapter we demonstrate that excellence is likely to emerge out of individual dynamic network-structures. The nodes consist of personal and environmental variables relating to a particular ability domain, and the connections are supportive or competitive effects of one variable on another. The network model we propose predicts typical developmental properties such as idiosyncratic routes to excellence, and predictive indicators of later ability, the reliability of which increases with age. In addition, the model accurately predicts the highly right-skewed distributions of productivity across the population, which occur in virtually any achievement domain (e.g., publications of scientists, medals won by athletes, etc.). Finally, we illustrate how the model can be fine-tuned to generate plausible predictions in the domain of sports (i.e., soccer and tennis). The finding that excellence likely emerges from individual compositions of dynamic networks has implications for future approaches to the detection and stimulation of excellence in different achievement domains.

6.1 Introduction

Relatively few people develop excellence, and in rare instances individuals reach exceptional levels of success, such as Albert Einstein, Mozart, and Roger Federer. Excellence refers to domain-specific superiority, and is a topic that has been extensively studied in the domains of science, music, technological creativity, and sports (e.g., Ericsson & Charness, 1994; Howe, Davidson, & Sloboda, 1998; Kaufman, 2013; Macnamara et al., 2014; O'Boyle & Aguinis, 2012; Simonton, 1999, 2001). Ever since the topic was introduced, debate has existed on the origins of excellence. This debate already started in the 1860s, when Galton published his work on the genetics of genius, claiming that excellent performers are born (Galton, 1869). In 1873, following Galton's work, De Candolle wrote a book in which he stated that environmental resources (e.g., family, education, facilities) are the major factors explaining the development of excellence (De Candolle, 1873). In addition to these classical nature and nurture points of view, Ericsson and colleagues demonstrated more recently that prolonged and intensive practice, often more than 10 years, is necessary to reach excellent levels of performance (e.g., Ericsson, 2006; Ericsson & Charness, 1994; Ericsson et al., 1993).

While the debate on the exact role of nature and nurture continues (e.g., Detterman, 2014; Kaufman, 2013), most researchers agree that all such factors (genetic endowment, tenacity, parental support, help from coach or teacher, practice, etc.) contribute to the development of excellence (e.g., Abbott, Button, Pepping, & Collins, 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Gagné, 2004; Elferink-Gemser, Jordet, Coelho-E-Silva, & Visscher, 2011; Hambrick & Tucker-Drob, in press; Howe et al., 1998; Kaufman, 2013; Phillips et al., 2010; Simonton 1999, 2001, 2003; Vaeyens, Lenoir, Williams, & Philippaerts, 2008). However, how the different factors actually combine to shape excellence over time remains unknown. In the current chapter, we focus on the underlying model principles that explain, and predict, some major properties of excellence. That is, rather than attempting to determine the specific contribution of factors related to excellence across the population, we will focus on the kind of (generic) model that gives rise to typical characteristics of excellence as they are found in different achievement domains. We will propose that excellence is likely to emerge out of idiosyncratic networks of connected personal and environmental variables that are in continuous interaction. In addition, we will demonstrate how the network model can be fine-tuned to fit with a specific performance domain, namely sports.

Properties of Excellence Development

The emergence of excellence covers a developmental range from the moment that a domain-specific ability starts to grow (i.e., beginner level) until the point that superior performance is (repeatedly) demonstrated (e.g., Abbott & Collins, 2004; Howe et al., 1998; Simonton, 2001; Phillips et al., 2010). Recent literature stipulates that, across achievement domains, the developmental trajectories leading to excellence are characterized by a number of qualitative properties (for an overview, see Simonton, 2001). First, in different individuals a similar ability can emerge at different ages, evidence for which is found in the domains of music (e.g., Howe, Davidson, Moore, & Sloboda, 1995; McPherson & Williamon, 2006; Sosniak, 1985; 1990), arts (e.g., Sloane & Sosniak, 1985), mathematics (e.g., Gustin, 1985), and sports (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin, Weissensteiner, Oldenziel, & Gagné, 2013; Phillips et al., 2010; Vaeyens et al., 2008). Second, the underlying constituents of a particular ability can change during the individual's life span (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Davids & Baker, 2007; Elferink-Gemser, Huijgens, Coelho-E-Silva, Lemmink, & Visscher, 2012; Howe et al., 1998; Simonton, 1999, 2001; Phillips et al., 2010). Third, the level of domain-specific ability is not necessarily monotonically rising or stable: Its development can take a variety of forms including gradual, S-shaped, stepwise, and sudden changes (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Dai & Renzulli, 2008; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin et al., 2013; Simonton, 1999; 2001; Phillips et al., 2010; Simonton, 2000; Vaeyens et al., 2008). Fourth, early indicators of ultimate excellent abilities are often absent, which means that demonstrating better skills than peers at a young age is often weakly related to later excellent abilities (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999, 2001; Vaeyens et al., 2008). In line with the latter three properties, research—particularly in the domain of sports and exercise—has shown that individuals may have diverse ways to achieve similar ability levels, thereby emphasizing the idiosyncratic nature of the pathways to excellence (e.g., Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin et al., 2013; Phillips et al., 2010; Simonton, 2000; Vaeyens et al., 2008).

Validated tests to determine domain-specific excellence hardly exist, and researchers often focus on assumed correlates of a particular ability (e.g., dribbling test-scores of soccer players, Huijgen, Elferink-Gemser, Post, & Visscher, 2009). Here, we proceed from the argument that excellent abilities are domain-specific and that they are manifested in, and measured by, performance accomplishments (Aguinis & O'Boyle, 2014). In many domains (e.g., arts, science, sports, technology, music, etc.), performance accomplishments can be operationalized by individuals' productivity as defined by consensual expert assessment (e.g., Amabile, 1982, 1983, 1996). The consensual assessment technique implies that the quality of human performance can be judged by experts in a particular domain (e.g., reviewers of a research article, coaches of sport teams) and/or based on countable expressions of particular excellent abilities, such as produced scientific articles, musical compositions, and tournaments or medals won in sports (e.g., Aguinis & O'Boyle, 2014; Huber, 2000; O'Boyle & Aguinis, 2012; Simonton, 1999, 2003, 2014). A measure of productivity, based on consensual expert assessment, thus emphasizes what a performer has realized in a particular performance domain, and is a widely used operationalization of excellent abilities. In line with Ericsson and Lehman's (1996) definition of expertise, this measure reflects who displays (or has displayed) consistent superior performance. Productivity is also considered a valid indicator of domain-specific ability in practice, in that it is used as a selection criterion in job interviews, decisions about grant proposals, and national selection of athletes for international competitions. For instance, to select soccer players for the national team before the world cup, the coach will not let players perform a (standardized) test of an assumed soccer-ability correlate. Probably, the coach will select players based on relevant productivity indicators (e.g., number of matches played, number of goals scored).

Previous studies have shown that the distribution of performance productivity across the population is highly right-skewed in virtually any achievement domain (e.g., Huber, 2000; O'Boyle & Aguinis, 2012; Simonton, 1999, 2001, 2003). Earlier studies based on archival data have shown that the relationship between a particular number of products—e.g., medals won in sports, scientific publications in high-impact journals, patent inventions—and the number of individuals generating that number of products, approaches distributions described by power laws or stretched exponentials (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Huber & Wagner-Dobler, 2001; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Sutter & Kocher, 2001). This finding entails that the great majority of performers has few products (often only one), whereas the truly exceptional performers are in the extreme right tail of the asymmetric distribution. As an illustration, Figure 13 displays the distributions of two (historical) datasets, one of which concerns the number of international matches played by Dutch soccer players in the National team (retrieved from Voetbalstats.nl), and the other the number of ATP tennis tournaments won by tennis players (retrieved from ATP Performance Zone). In line with earlier literature, these distributions are highly skewed, and on a natural log-log scale they approach a linear plot (power law) or curved plot (stretched exponential).

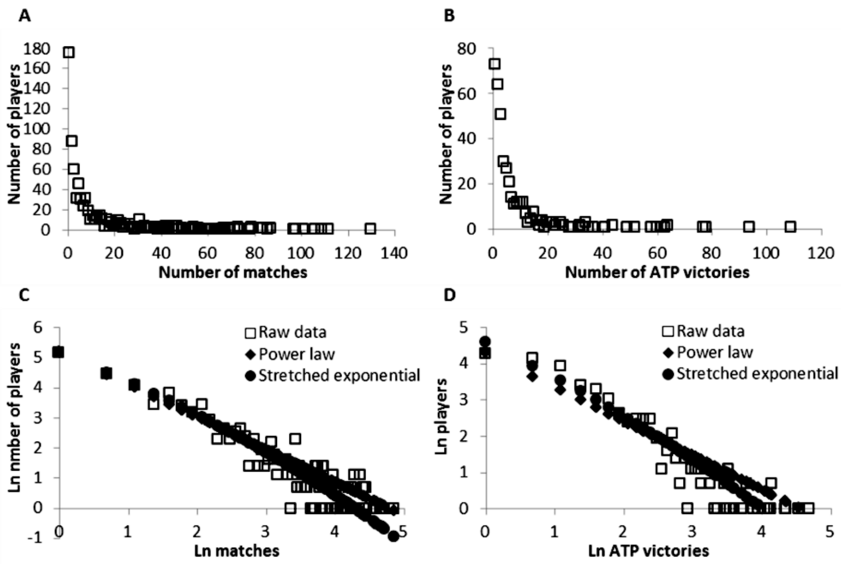


Figure 13. Distributions of the number of international matches a soccer player played in the national team (A), and the number of ATP tennis tournaments won by tennis players (B). The natural log-log plots of these datasets are displayed in Graph C and D.

Towards a Model of Excellent Human Performance

Based on the accumulated knowledge with regard to talent and excellence development, the challenge is to establish a model that is multidimensional (Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gagné, 2004; Kaufman, 2013; Phillips et al., 2010; Simonton, 2001), and able to predict and explain the growth of domain-specific abilities that lead to a level at which products are generated. Hence, our aim is to provide insights into what kind of model drives the emergence of the typical idiosyncratic developmental properties, as well as the highly skewed productivity distributions across the population, at the level of excellent human abilities and performance.

Because excellence typically develops over time (often over more than 10 years; Ericsson, 2006; Ericsson et al., 1993; Ericsson, Roring, & Nandagopal, 2007), we propose a dynamic model of growth to account for a performer's ability development (cf. Van Geert, 1991, 1994). Such models have not yet been applied to talent and excellence development, although some authors already hinted toward their value (e.g., Aguinis & O'Boyle, 2014; Abbott et al., 2005; Abbott & Collins, 2004; Araújo & Davids, 2011; Ceci, Barnett, & Kanaya, 2003; Dai, 2005; Dai & Renzulli, 2008; Davids & Baker, 2007; Phillips et al., 2010). In line with the consensus that excellence is shaped by various (interacting) personal and environmental variables, we will demonstrate a dynamic network model, according to which excellent abilities emerge from the iterative interactions among sparsely—and across the population randomly—connected network variables, which may correspond to domain-specific ability, motivation, parental support, teaching and coaching, practice, and so forth.

A Dynamic Network Model Representation of Ability Development

An ability network consists of one node (i.e., variable) representing the domain-specific ability, and other nodes consisting of components that positively or negatively affect the ability (and each other). In line with the existing models in the field of talent and excellence development (e.g., the Differentiated Model of Giftedness and Talent; Gagné, 2004), the nodes can be of an internal or of an external nature, such as domain-specific interest and family support, respectively.

Connections between the variables may be supportive or competitive, symmetric or asymmetric, and direct or indirect. An example of a direct, symmetric connection is the positive feedback-loop between the growth of an ability (e.g., tennis ability), and the amount of practice (Figure 14A). However, connections can also be indirect or asymmetric, for instance when the coach positively affects the tennis ability, which in turn positively affects parental-support; in this case the support of the coach and the support of the parents are indirectly connected (Figure 14B). We propose that any variable in the network is directly connected with a relatively small number of other variables and indirectly connected with a considerably greater number of other variables (cf. Watts & Strogatz, 1998).

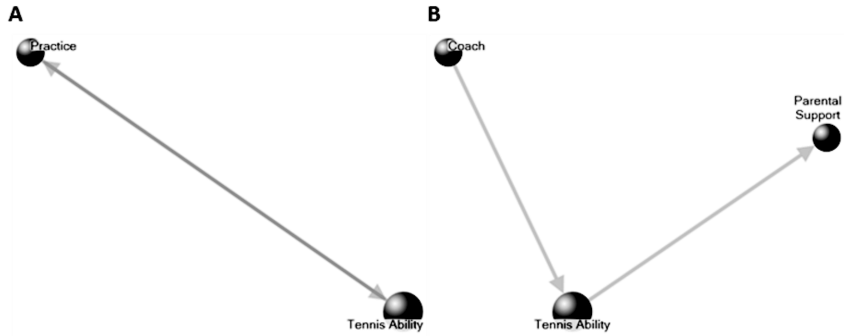


Figure 14. Examples of a direct, symmetric connection between two variables (Graph A) and an indirect asymmetric connection (Graph B). Such compositions form the building blocks of the entire dynamic network.

The network is dynamic in the sense that the values of the nodes (the levels) change, among others as a consequence of the interactions with other nodes, and nodes may appear or disappear over developmental time (cf. Barabási, 2009). The nature and strength of the relationships between the ability component, the internal components, and the external (environmental) components are assumed to be idiosyncratic and characteristic of a particular person's dynamic network profile (specificity of ability profile and individual differences are characteristic of excellent performance in general, e.g., Achter, Lubinski, & Benbow, 1996; Elferink-Gemser et al., 2011; Phillips et al., 2010;

Robertson, Smeets, Lubinski, & Benbow, 2010; Vaeyens et al., 2008; Webb, Lubinski, & Benbow, 2002; for a general discussion of the importance of idiosyncratic models, see Molenaar, 2004; Molenaar & Campbell, 2009).

To provide an example, a dynamic ability network can be visualized as follows. Imagine that a particular child has a particular interest in tennis. The parents of the child recognize this and strongly stimulate this interest. To the extent that their child shows more interest, the parents tend to buy a new racket, take the child to the tennis court, pay his training/coaching, etc. The child’s practice and tennis ability are reciprocally related: As the child's tennis level increases, practice increases and vice versa. Furthermore, the child also experiences considerable pleasure because of playing tennis, and is very persistent. This pleasure and tenacity increase as the tennis ability increases. Then, at secondary school, the child meets new friends who like to hang out after school. After having joined once, the child obtains more support from the friends, for instance in the form of increasing popularity in the group. In this particular network, hanging out with friends competes with tennis ability development, for instance through a competition for available time or through a competition between motivation for gaining popularity and motivation for playing tennis.

If we now take a look at this individual’s tennis ability network, the interconnected variables can be displayed in the form of a directed graph consisting of nodes and arrows (Figure 15). The nodes specify the relevant variables, such as the child’s motivation to hang out with friends after school or the pleasure it experiences when playing tennis, that influence or are influenced by other variables in the network. The sizes of the nodes reflect the levels (or strength) of the variables. Each directed edge between two nodes represents a supportive (solid) or competitive effect (dashed) of one variable on another. The strength of the relationships between the variables is reflected in the thickness of the edges.

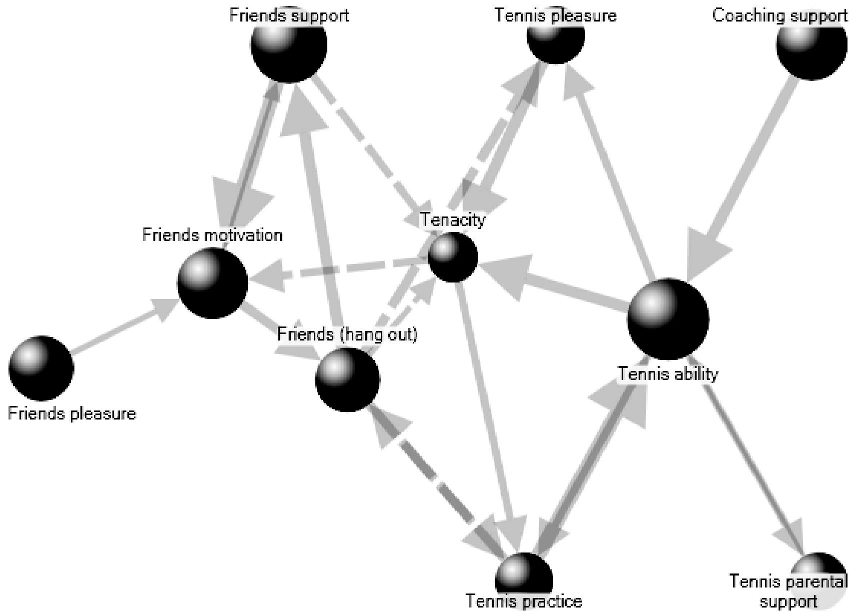


Figure 15. Graphical representation of an individual's tennis ability network structure.

Mathematical Principles of the Dynamic Network Model

When focusing on the mathematical principles of the network structure, the various nodes and their connections are expressed in the form of equations. The domain-specific ability corresponds to one equation, and its growth depends on: (1) the ability level (*L*) already attained, (2) available resources that remain relatively constant during ability development (*K*) such as genetic endowment of the ability, (3) resources that vary on the time scale of ability development (*V*), such as parental, teaching or coaching support, practice, and tenacity, (4) the degree in which an ability profits from the constant resources (*r*), (5) the positive, negative, or zero weights of the connections (*s*) with the variable resources, and (6) a general limiting factor (*C*) (Van Geert, 1991; 1994). The *C*-parameter is the carrying capacity, which specifies the ultimate or physical limits of growth of a particular variable. In other words, the *C*-parameter keeps the variables within (physically) realistic limits, in the relatively unlikely case that too many relationships are strongly positive and drive a variable (e.g., ability) into an exponential explosion (e.g., Van der Maas et al., 2006). Within the ability network, the variable resources (*V*) are potentially co-dependent on the ability and on any arbitrary subset of all other variables. Taken together, our model thus implicitly follows a gene × environment approach, that is, the model specifies a multiplicative relationship between the ability-specific *K*-parameter (genetic endowment), and the influence of the support-competition factors in terms of the variable resources (*V*).

The dynamic network model can be mathematically defined as a set of (sparsely coupled) logistic growth equations, each of which represents the growth of a single variable (*A*, *B*, *C*, and so forth), and one of which is the domain-specific ability. The number of variables to which a particular variable is connected, is represented by *i*, *j*, etc:

$$\left\{\begin{array}{c} \frac{\Delta L_A}{\Delta t} = \left(r_{L_A} L_A \left(1 - \frac{L_A}{K_{L_A}}\right) + \sum_{v=1}^{v=i} s_v \; L_A V_v\right)\left(1 - \frac{L_A}{C_A}\right) \\ \frac{\Delta L_B}{\Delta t} = \left(r_{L_B} L_B \left(1 - \frac{L_B}{K_{L_B}}\right) + \sum_{v=1}^{v=j} s_v \; L_B V_v\right)\left(1 - \frac{L_B}{C_B}\right) \\ \cdots \\ \cdots \\ \cdots \end{array}\right\} \quad (3)$$

From a model building perspective, we asked ourselves what are the minimal properties the network model should have for it to generate the qualitative features of the trajectories, as well as the highly skewed product distributions. To cover the structure of realistic domain-specific networks, our model has the following properties (note that a person's entire network may consist of multiple clusters, each representing a different performance domain, connected by variables functioning as hubs). In order to mathematically simulate individual's domain-specific networks, we start with a set of 10 nodes.[5] Within this network the nodes are sparsely connected with an average degree of connectivity of 25%, and the connections are randomly distributed over the nodes. This means that excellent abilities could emerge from different network configurations. For simplicity, for each simulation of an individual the initial parameter values are randomly drawn from symmetric distributions. The weights of the edges *s* are

[5] Network simulations based on up to 50 nodes reveal qualitatively similar results as simulations based on 10 nodes.

variable and randomly distributed with an average of zero. We identified one node (node 3) as the target variable whose change reflects the ability-development over time (for information about the specific parameter settings, see Method section).

The Current Study

In this study we aimed to test whether the typical properties of excellence emerge out of the dynamic network model described above, in order to discover the underlying principles of talent and excellence development. More specifically, if excellence emerges out of dynamic network structures, simulations of individual performers would reveal that: (a) similar ability levels can develop at different ages, (b) the underlying constituents of a the ability can change during the individual's life span, (c) the ability-development can take a variety of forms (e.g., gradual, S-shaped, stepwise, abrupt), and (d) early indicators of ultimate excellent abilities are often absent (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999, 2001). Furthermore, ever since the topic of excellent human performance was introduced, debate has existed on the contribution of heredity (for a recent intensive debate, see Ericsson, 2013; Ericsson, Roring, & Nandagopal, 2013; Gagné, 2013). Given that our model implicitly follows a gene × environment approach, in addition to examining the qualitative properties described above we also tested what the model predicts with regard to the role of genetic endowment.

Apart from testing the above-mentioned qualitative properties, by simulating many individuals we tested whether our dynamic network model predicts a major quantitative property of excellent performance, namely the highly skewed—power law and stretched exponential—distributions of productivity that are demonstrated by empirical data across many achievement domains (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Huber & Wagner-Dobler, 2001; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Sutter & Kocher, 2001). Additionally, we determined whether the distributions of excellent performance productivity can be (or are better) predicted by a null-hypothesis model based on the standard statistical assumption that abilities are normally distributed across the population, and are supported by the additive effects of *all* supporting variables.

Finally, apart from a general test of the dynamic network model, we considered it worthwhile to test the applicability of the model to a specific performance domain. For this aim, we took the empirical data that are displayed in Figure 13, and we tested whether the dynamic network model is able to predict the productivity distributions in the domain of sports (i.e., soccer and tennis).

6.2 Method

Default Model Settings

Each model simulation consists of 500 steps. The specific real-time duration of a single step thus depends on the domain of interest (e.g., a step length of about five weeks could be chosen for the domain of arts or science, in which ability growth and maintenance may cover a duration of about 50 years—around 2500 weeks—, whereas the step length can cover a shorter period in sports). For each simulation we defined the values of the parameters specified in the equations, by randomly drawing from predefined distributions. The actual parameter *values* have no intrinsic or absolute meaning, but are chosen in such a way that the total set of parameters allows us to run feasible simulations of lifespan trajectories, given the chosen number of simulation steps (e.g., Netoff, Clewley, Arno, Keck, & White, 2004; Van der Maas et al., 2006). Accordingly, the values of the parameters have their meaning in relation to each other, rather than to some absolute standard (Van Geert, 2014). This rationale follows from our aim to discover the general underlying model principles—such as the general connection structure of the network of components—from which excellence emerges, rather than already specifying the more or less exact values of the components as they may exist in domain-specific populations of excellent performers. Table 6 displays the default distributions from which the parameter values were drawn for each variable in the network.

Network Model Predictions of Developmental Properties

First, we ran network simulations of individual performers to examine the developmental patterns, including the growth curves (e.g., linear, S-shaped, stepwise growth; Van Geert, 1994) and the (changing) values of the network variables. This would provide information about the fit with the first three properties of excellence: Similar ability levels can develop at different ages; the underlying constituents of a specific ability can change over the individual's life span; and the ability-development can take a variety of forms. To test the fourth property—early indicators of ultimate excellent abilities are rare—, we determined the correlation between the end-ability levels and earlier levels. More specifically, we simulated 1,000 individuals and calculated correlation coefficients (Pearson *r*) between the end-level of node 3 (the ability component) and the level of node 3 at earlier simulation steps.

Finally, to explore the role of genetic endowment, we simulated 1,000 individuals and calculated the correlation (Pearson *r*) between the *K*-parameter of node 3 (the ability) and the actual ability level, during the simulated life-span of ability development.

Table 6. Default parameter values used for the dynamic model simulations.

Parameter	**Average**	**Standard deviation**
r (resource consumption rate)	.05	.01
Connection strength with other variables	0	.02
K (stable resources)	1.00	.15
Connection probability with other variables	.25	-
	Minimum	**Maximum**
L (initial level)	0	.05
Time of initial emergence of a variable	1.00	350.00
C (carrying capacity)	10.00	25.00

Network Model Predictions of Productivity Distributions

We assume that the domain-specific productivity of a performer is a function of the performer's (developing) ability level. However, apart from the ability level, a myriad of accidental events can occur with highly variable probabilities, which may or may not result in a product (e.g., Elferink-Gemser et al., 2011; Simonton, 2003). For instance, Steven Bradbury won the gold medal at the 2002 Olympic games, because the other competitors fell before the finish line, or imagine a researcher who finds unexpected results that lead to a high-impact publication (Simonton, 2003). Thus, in order to examine what the network model predicts concerning the productivity distributions we not only need a model of the underlying abilities, but also a model of how abilities lead to the products, which takes into account the stochastic nature of product generation.

The simplest model in this regard is the Poisson model, which states that the probability *P* that a particular product (e.g., a scientific paper or a tournament victory) will occur during a fixed time interval *t*, is the mathematical product of a domain-specific Poisson parameter (φ) and the individual's current level of the underlying ability *L* (Huber, 2000; Huber & Wagner-Dobler, 2001; Simonton, 2003). Hence, for each step in the simulation, there is a small probability that a product will be generated, and the number of products generated will accumulate across the simulated life spans. Because, in accordance with the empirical distributions, the majority of (excellent) performers in a specific domain has one product (e.g., Davies, 2002; Huber, 2000; Lotka, 1926; O'Boyle & Aguinis, 2012; Sutter & Kocher, 2001), the probability that a product is released during each time step is chosen in such a way that the average productivity during an entire life span is 1. The Poisson parameter that corresponds with this lifetime average is .002, since the simulation length was set at 500 steps. At a particular moment during ability development, the probability of generating a product is thus predicted based on the following equation:

$$P_t = 0.002 \times L_t. \tag{4}$$

To determine the validity of the dynamic network model, we compared the simulation results with the properties of the empirical product distributions as found across domains (i.e., sports, science, music, etc.).

Null-Hypothesis Predictions of Productivity Distributions

To provide an additional test of the dynamic network model, we compared the network model predictions with predictions based on simulations of a null-hypothesis model. If the null-hypothesis model generates a comparable (or better) fit with the empirical data, we should opt for the null-hypothesis model in view of its greater simplicity. The null-hypothesis model rests on the standard statistical assumptions that abilities are normally distributed across the population, and are supported by the additive effects of all supporting variables, such as tenacity, coaching, and practice. We therefore reduced the connection strength with other variables in the network to 0, and we treated the *K*-parameter of the ability variable as the parameter including *all* resources to develop excellence:

$$\frac{\Delta L}{\Delta t} = r\, L\, (1 - \frac{L}{K}) \tag{5}$$

Network Model Predictions of Domain-Specific Distributions

In order to test the applicability of the dynamic network model in a specific performance domain, we focus on the domain of sports. In sports, support resources (e.g., parental and coaching support, facilities) play a relatively large role in athletes' developments (e.g., Baker, Horton, Robertson-Wilson, & Wall, 2003). Moreover, apart from the ability component, the tenacity component (goal commitment, perseverance in a specific sport) is assumed to be a major determinant of productivity (Abbott et al., 2005; Abbot & Collins, 2004; Van Yperen, 2009). Accordingly, we adapted the default parameter settings displayed in Table 6 by reducing the *K*-parameter from 1.00 to 0.50 (*SD* = 0.15) and extending the range of the variable support contribution (*SD* = 0.10). This means that we increased the influence of the variable support resources relative to the stable resources (e.g., genetic endowment). Furthermore, in the network model we selected one node (node 4) as the tenacity component, and we used an ability (*L*) × tenacity (*T*) product model (Huber, 2000; Huber & Wagner-Dobler, 2001). This means that the probability of generating a product at time *t* is a function of the *combination* of ability (*L*) and tenacity (*T*):

$$P_t = \varphi L_t T_t, \tag{6}$$

where the Poisson parameter was set at 0.005.

We focused on productivity measures in two major sports: Soccer and tennis. In both sports we assessed historical productivity data based on consensual expert assessment, namely the number of matches played in the Dutch national team by soccer players, and the number of ATP tournaments won by tennis players, which are displayed in Figure 13. To optimally compare the generated distributions, we plotted the data on natural log-log scales, and we set the number of players with one product equal to 1.

6.3 Results

Developmental Trajectories towards Excellence

Figure 16 provides a representative illustration of two simulated individuals who reach high ability levels. The Figure illustrates that the same type of ability can emerge at different ages, and that the same ability can be the product of different (changing levels of) underlying variables. In addition, we can observe that the ability levels are not monotonically rising or stable. Note, however, that the ability levels are latent variables here, which cannot be observed directly. As noted earlier, levels of (excellent) ability that individuals attain are manifested stochastically via the number of products they are associated with (see next section).

In Figure 16, Graph A displays an individual's simulated ability network in which the ability level reaches a value of 3.91 (2.85 standard deviations above the average simulated population ability level of 1.26), and Graph B shows an individual's ability network in which the ability level reaches a value of 4.48 (3.46 standard deviations above the average simulated population ability level). The simulated individual in Graph A displays a clear increase in ability level early in development, which stabilizes around step 320, whereas the ability level of the individual in Graph B starts to rise slowly, and shows a steep increase around step 320. In addition, the simulations revealed that new variables can emerge at various moments during development, which may influence the trajectory of ability development. For instance, variable 10 emerges relatively late in individual B, and seems to contribute to an abrupt increase in the ability in this specific individual. Finally, the growth curve of individual A resembles a gradual stepwise growth, whereas individual B displays an S-shaped growth including abrupt change.

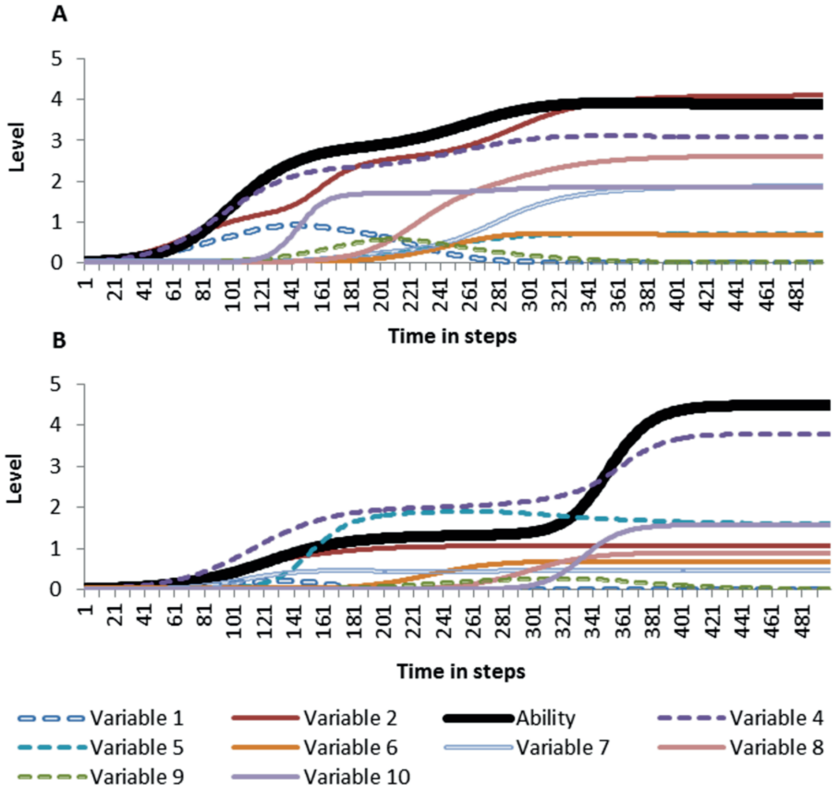


Figure 16. Simulations of the ability networks of two individuals (A and B). The black solid lines in the graphs represent the abilities, the other lines reflect the dynamic network variables that have supportive, competitive, or neutral relationships with the ability.

To test what the model predicts with regard to early indicators of later performance, we simulated 1,000 different individuals. For simplicity, we expressed the simulation steps in terms of age (i.e., an age range from 0 to 44 years, which is typical for domains such as science and arts). Results show that the correlation between the end-level of the ability and its level in early childhood is virtually absent (Figure 17). However, we can also observe that around the simulated age of 12, the correlation has increased to 0.5, after which it further increases to approximately 1. Thus, although we find a low correlation between the end level and early levels of ability, we also find that the correlation between the end ability-level and earlier levels increases with age.

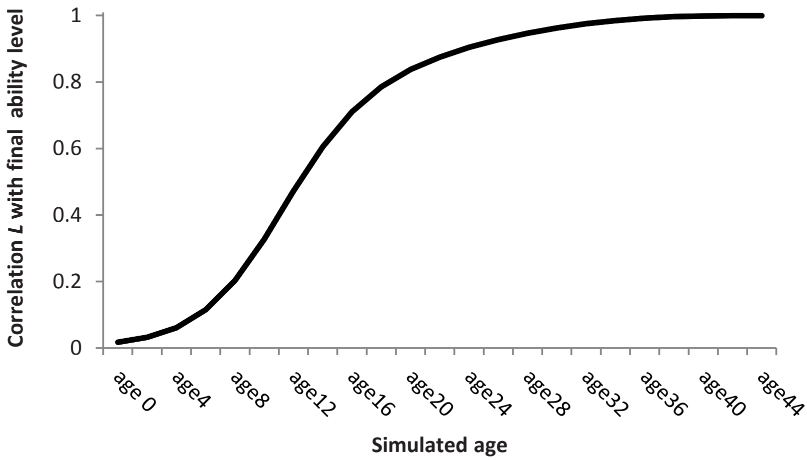


Figure 17. Correlations between the final ability level and earlier levels.

Finally, to determine the model predictions with regard to the role of genetic endowment, we calculated the correlations (Pearson *r*) between the *K*-parameter of node 3 and the ability level. Simulation results revealed that the correlation is around 0 at the beginning, increases to about 0.5, and then falls back to stabilize around 0.4 (Figure 18).

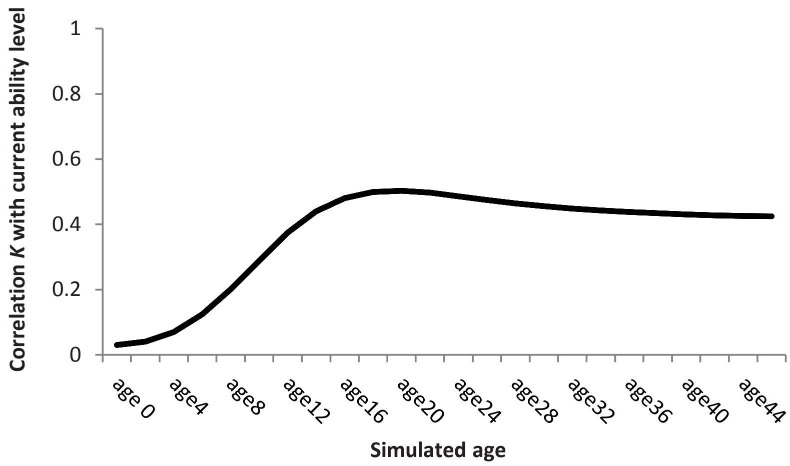


Figure 18. Correlations between the *K*-parameter and the ability level at different simulated age-steps.

General Predictions of Productivity Distributions

Our simulations based on 100,000 runs with the default parameter values show that the network model generates highly right-skewed product distributions. In order to determine whether the predictions are specific to the dynamic network model, we compared the results with simulation results of the null hypothesis model. To guarantee that the null hypothesis model would produce the same average ability level as the network model, the level of *K* was augmented to 1.26, which equals the average ability level resulting from the network model (note that the average ability level resulting from the network model simulations was 26% higher than what would be genotypically expected based on the settings of the *K*-parameter; a value of 1). Although the simulations based on the null-hypothesis model also produced skewed product distributions, they did not generate the typical power law or stretched exponential distributions that were generated by the dynamic network model. Figure 19 also shows that the right tail of the product distribution generated by the network model is considerably longer than that of the null hypothesis model (a maximum of 25 versus 8 products).

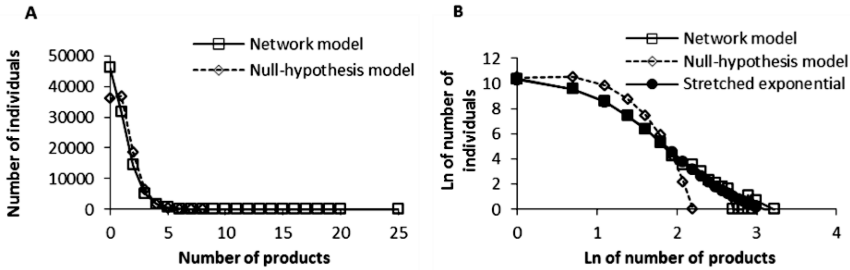


Figure 19. Simulated product distributions of the network model and the null-hypothesis model. Graph A displays the raw frequencies; in Graph B the data are plotted according to the natural logarithmic scales.

Additionally, we tested whether the parameters of the null-hypothesis can be adapted in a way that it would also produce the highly skewed distribution in line with the empirical data. In order for the null hypothesis model to generate maximum number of products comparable to that of the network model, we had to set a seven-times bigger Poisson parameter, but also an average value of the *K* parameter that is 25% higher, and a standard deviation of the *K* parameter that is twice as big. However, with these parameter settings the average number of products in the population would be about 10 times bigger than generated by the network model, with a distribution that is almost symmetrical.

Domain-Specific Predictions of Productivity Distributions

Figure 20 displays the log-log plot of the empirical productivity measures in soccer and tennis and the predictions of the network model simulation, as based on the adapted parameter values (see Method section). In line with the empirical data of the number of matches played in the Dutch national team (soccer) and the number of ATP tournaments won (tennis), the simulation revealed a highly comparable distribution that approaches a straight line (i.e., a power law).

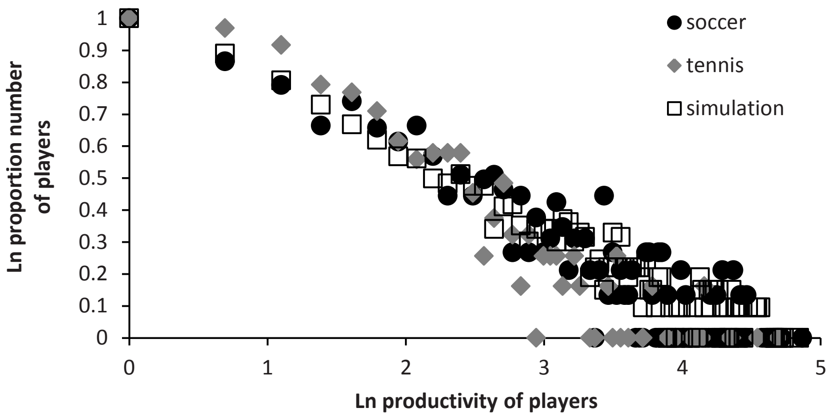


Figure 20. Ln-Ln graph of productivity in soccer, tennis, and according to simulation.

6.4 Discussion

Since the 1860s, philosophers, researchers, and policy makers have been intrigued by the question how excellent human performance can be explained and predicted (Kaufman, 2013). Although research has advanced insights into the components (i.e., nature, nurture) that contribute to excellence (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Davids & Baker, 2007; Ericsson & Charness, 1994; Ericsson et al., 1993; Howe et al., 1998; Kaufman, 2013; Phillips et al., 2010; Simonton, 1999; 2001; 2003; Vaeyens et al., 2008), debate continues to exist on the exact role of nature and nurture (Kaufman, 2013). Related to this, the dominant research practice has been based on finding associations between individual and environmental predictor variables on the one hand and performance on the other, as they statistically exist within the population (Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Elferink-Gemser et al., 2011; Howe et al., 1998; Kaufman, 2013; Simonton, 1999; 2001; 2003; Vaeyens et al., 2008). As yet, however, researchers have not been able to capture and explain the time serial, individual-based developments towards excellence. Here, we propose a dynamic network model to explain the qualitative properties of excellence development, which are (a) in different individuals a similar ability can emerge at different ages; (b) the underlying constituents of a particular ability can change during the individual's life span; (c) the level of domain-specific ability is not necessarily monotonically rising or stable: Its development can take a variety of forms; and (d) early indicators of ultimate excellent abilities are often absent (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Simonton, 1999; 2001; Phillips et al., 2010; Vaeyens et al., 2008). In addition, we tested whether the network model predicts a typical quantitative property, namely the highly right-skewed distribution of productivity that occurs in virtually any achievement domain, and that can be described by power laws and stretched exponentials (e.g., Huber, 2000; O'Boyle & Aguinis, 2012; Simonton et al., 1999; 2001; 2003).

Developmental Properties of Excellence

The model simulations revealed idiosyncratic routes to excellence, and more specifically that the same ability level can be attained in different ways; that the values of the (in)directly coupled (supportive or competing) variables change over time; and that the ability growth curve can take different forms for different simulated individuals. These model predictions correspond exactly to the first three properties of excellence development (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Simonton, 1999; 2001; Phillips et al., 2010; Vaeyens et al., 2008). Furthermore, we found that the relationship between early ability levels and the end level was virtually absent, which supports the fourth property of a lack of early predictors of later excellence (Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999; 2001; Vaeyens et al., 2008). However, the simulations also revealed that the relationship increases with age, and is around 0.5 at the simulated age of 12. This is in accordance with several studies, mostly in the domain of scientific talent, that showed at least moderate to good predictability of later excellence around adolescence (e.g., Lubinski, Benbow, Webb, & Bleske-Rechek, 2006; Lubinski, Webb, Morelock, & Benbow, 2001; Wai, Lubinski, & Benbow, 2005).

When examining the role of genetic endowment, we found that the relationship between the genetic (*K*) component and ability first increased to a value around 0.5, after which it decreased and stabilized around 0.4 during the remainder of ability development. This model prediction is qualitatively in line with several studies, mostly on cognitive and scientific talent, having demonstrated an increase in heritability during childhood (Devlin, Daniels, & Roeder, 1997; Haworth, Dale, & Plomin, 2009). A recent extensive twin-study found that the heritability of scientific performance increases to 64% around the age of 9, after which it decreases to 47% around the age of 12 (Haworth et al., 2006). The authors suggested that the drop is caused by the increase in environmental effects on performance over time. This finding and the suggested explanation are consistent with the network model, in which potentially competitive or supportive variables are added to the network as age increases (see Table 6).

Thus, based on model simulations, we find that the characteristic developmental properties of excellence emerge out of idiosyncratic networks of mutually supporting or competing variables, such as abilities, tenacity, external support, and practice. Furthermore, as the network-model predictions suggest, internal, environmental, and practice components should not be considered as separate mechanisms to explain excellence, but as factors whose functional role is embedded in a network consisting of multiple dynamic and sparsely connected variables. Although our simulation results thus support the plausibility of the dynamic network model to explain excellence development, we shall also discuss the extent to which the network model predicts existing empirical data on population distributions of excellent performance in different domains.

Distributions of Excellent Performance Across the Population

A major property of excellence at population-level, is that the distributions of performance productivity are highly right-skewed. Simulating a population of (excellent) performers, the network model predictions revealed a highly-skewed productivity distribution that can be fitted by power law and stretched exponential functions, and is qualitatively similar to the distributions found in wide variety of domains, including science, music, arts, technology, and sports (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Simonton, 1999; 2003; Sutter & Kocher, 2001). The simulations of a null-hypothesis model, based on the assumptions that abilities are normally distributed across the population, and are supported by the addition of relevant resources (e.g., teaching and coaching, practice, tenacity), generated productivity distributions that did not come near the distributions of the empirical data. Moreover, the parameter settings could not be adapted in a way that also the null-hypothesis model revealed the highly skewed product distributions. These results provide strong additional indications for the validity of our dynamic network model of excellence.

In addition to testing the dynamic model predictions based on the default parameter settings, we also fine-tuned the settings to the domain of sports. In line with the universality of highly right-skewed distributions of performance productivity across domains, the product distributions—based on consensual expert assessment—in soccer and tennis were also highly skewed. To predict the distributions of the number of matches played in the national team (soccer) and the number of ATP tournaments won (tennis), we adapted the model settings according to the sports literature (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Baker et al., 2003; Van Yperen, 2009). With an ability – tenacity Poisson model connected to the network model, the predictions closely corresponded to the empirical data. This suggests that the dynamic network model not only qualitatively fits across domains, but is also applicable within specific performance domains, including sports.

Conclusion and Future Directions

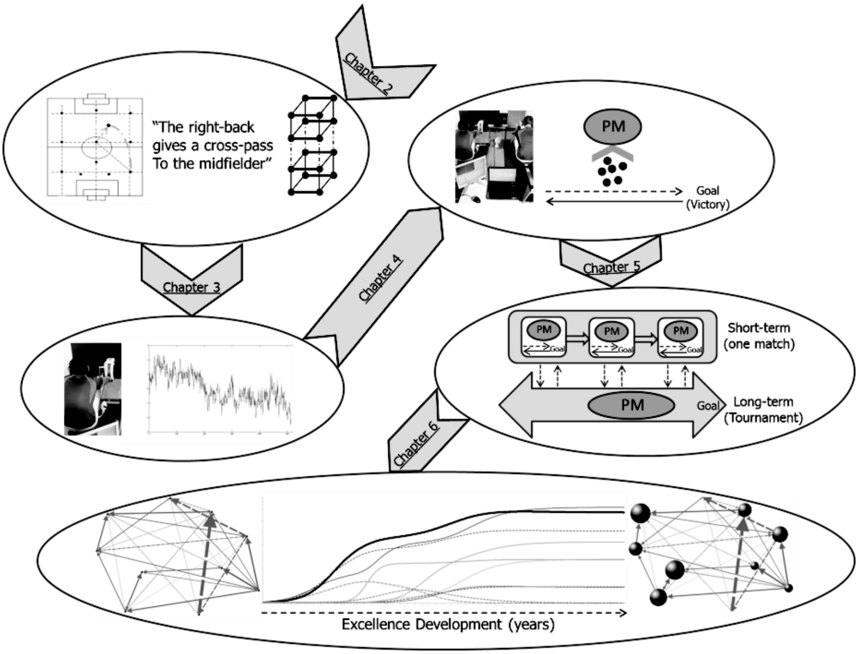
The relatively simple dynamic network model we propose seems to provide a comprehensive framework to understand the kind of principles, or mechanism, underlying the development of excellence across different domains, such as science, arts, music, and sports. The model suggests that excellence emerges from intra- and inter-individual variations in the composition of idiosyncratic dynamic networks. Although we departed from a general foundational model, the model can be used and fine-tuned to discover the more specific dynamic principles underlying excellent performance in one particular domain of interest (e.g., sports).

The discovery that excellence likely emerges from idiosyncratic network structures may have widespread implications for theory and practice. For instance, it casts doubt on the assumption that the ability to reach excellence can be detected ‘in the individual’, and must be discovered at an early age. This perspective still dominates the talent detection programs in research and practice around the world (for comparable accounts, see Abbott et al., 2005; Abbott & Collins, 2004; Ericsson et al., 1993; Howe et al., 1998; Phillips et al., 2010; Vaeyens et al., 2008). However, in line with several authors' propositions (Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Lubinski et al., 2006; Lubinski et al., 2001; Simonton, 1999; 2001; Vaeyens et al., 2008; Wai et al., 2005), our network model predictions show that early indicators of later performance are virtually absent (yet increase with age), and that various kinds of direct and indirect multiplicative relationships between dynamic variables may exist and lead to idiosyncratic routes to excellence.

Although empirical studies that focus on individual developmental patterns toward excellence are scarce, researchers start to acknowledge that idiosyncratic patterns are the rule rather than the exception (e.g., Elferink-Gemser et al., 2011; Gulbin et al., 2013). For instance, in the Groningen talent studies, athletes have been longitudinally followed to study the development of several ability-related variables. Various papers based on this research program reported average differences between ultimately successful (professional) and non-successful athletes. To give an illustration, ultimately successful soccer players would outperform their non-successful counterparts on dribbling skills by the age of 14 (Huijgen et al., 2009), on interval endurance capacity from the age of 15 (Roescher, Elferink-Gemser, Huijgen, & Visscher, 2010), and on tactical skills at the age of 17 (Kannekens, Elferink-Gemser, & Visscher, 2011). However, the researchers acknowledge that the athletes had their own unique patterns toward successful (excellent) performance, which should not be omitted (Elferink-Gemser et al., 2011). In order to advance research on excellent performance, future studies should thus focus on the individual developmental patterns (see Gulbin et al., 2013), and acknowledge that these emerge from continuous mutual interactions between network variables, rather than from the addition of causal variables that explain a significant portion of performance variance at the sample level.

Finally, from a practical standpoint, although it is not easy to detect (or manipulate) what is inherently complex, it is possible to create conditions under which the probability of developing excellence can be increased. Accordingly, the basic practice of the 'sowers of excellent performers' (e.g., coaches, teachers, parents) should reside in: (a) their creativity of combining possibilities into a pattern that is optimally excellence-eliciting, such as by providing appropriate support (e.g., Van Geert & Steenbeek, 2005) and (b) their ability to see the signs in the individual, and in the individual's environment—e.g., enthusiasm, goal commitment, social support—that signal the opportunities for creating the (network) conditions under which excellence may develop.

Chapter 7: Summary and General Discussion



7.1 Introduction

In this thesis a diversity of topics related to human performance processes has been discussed in light of one common denominator: Complexity (see Table 1 in the Introduction section). More specifically, the main focus was on the emergence of coherent states or patterns out of the interactions between lower-order components. These processes were primarily studied in sports, a typical context in which ongoing psychological and performance processes take place that can relatively easy be observed and measured (Day et al., 2012). We proposed that complex processes could be captured using specific research designs and methods inspired by the theory of complex dynamical systems (e.g., Davids et al., 2014; Kelso, 1995; Nowak & Vallacher, 1998; Van Geert, 1994).

Although the complexity approach differs from the conventional reductionist paradigm to the study of human behavior—in which explanations for behavior can be reduced to some underlying causal components—, the complexity perspective touches on fundamental theoretical assumptions already proposed in the previous century. For instance, Lewin (1935) emphasized that individual and environmental factors do not operate independently; they interact. Moreover, he stated that the relationships between these factors change over time, which is why we may characterize them as complex dynamical processes. In general, researchers will probably not deny that behavior takes place in a context of many interacting personal and environmental factors that undergo change. Most researchers, however, would argue that this complexity makes precise prediction of behavior nearly impossible (Gill & Williams, 2008). Therefore, in order to explain and predict human psychological and performance states as accurately as possible, most studies examine a selection of potential determinants in isolation, either at one moment or across a few time points. That is, the conventional approach is to untangle the complicatedness of a certain state by reducing the explanation of that state to the additive influences of (isolated) causal components (see Introduction).

Rather than studying (potential) determinants in isolation, this dissertation proceeded from the viewpoint that individual and environmental factors continuously interact and change over time, which results in particular psychological and behavioral patterns. That is, we assumed that the underlying mechanism that explains human performance processes is complex. Chapter 2 started with a study on the complexity of cognitive skills, embedded in verbalizations while watching video clips of game plays. In Chapter 3 we proceeded with a study on the underlying dynamic organization while athletes are performing an actual sports task. In the Chapters 2 and 3, we thus extracted a complexity measure of two different kinds of processes, and we examined how these were related to expertise. In Chapter 4 and 5 we proceeded from the assumption that psychological momentum (PM) is a complex phenomenon emerging during goal striving. We examined patterns in collective psychological and behavioral performance variables that are characteristic of PM, during periods in which athletes progressed or regressed in relation to their goal. Finally, in Chapter 6 we focused on macro-level patterns, that is, developmental trajectories of excellence, and on the specific underlying dynamics in the form of mathematical equations. In this way we tested our assumption that excellent human performance emerges out of complexity, that is, ongoing interactions between multiple performance-related variables (e.g., motivation, practice, family support). Together, the different chapters thus shed light on the complexity of performance-related processes across different levels and time scales (from bodily processes during a single sports task to ability development over the course of a career). The next section provides a brief overview of the findings of each chapter.

7.2 What Did We Find?

Chapter 2

We started with an empirical study on the complexity of representations as they are constructed in real-time by soccer players, who were exposed to offensive game plays. Such representations are assumed to emerge from the integration of pieces of information, such as the positions and movements of other players on the soccer field (e.g., Helsen & Starkes, 1999), or details of the actions carried out (e.g., McPherson, 2000). Previous research found that expert soccer players generate a greater number of verbal report statements, evaluate the situation more often, and look at informative locations on the field (e.g., scanning elements or areas surrounding the player having the ball). Hence, previous research primarily focused on specific components that expert players notice, and which potentially explain their superior perceptual-cognitive skills (e.g., Roca et al., 2011). Yet, how soccer players integrate the components at particular levels of complexity has remained unknown and may shed a new light on cognitive skills, and their relation with expertise.

We used Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) to construct a coding system (De Meij, Van der Steen, & Den Hartigh, 2012), so that we could reliably determine the complexity levels of the representations that were formed by soccer players with different levels of expertise: Experts (professionals), near-experts (high amateurs), and non-experts (low amateurs). Based on verbalizations that soccer provided while watching soccer game plays, we were able to assess players' short-term representations. We found that players with higher levels of expertise constructed their representations at higher complexity levels. In addition, when constructing their representations, players with more expertise described information excluding the player with the ball (off-the-ball movements, defending actions) relatively more often at high complexity levels.

Thus, Chapter 2 illustrated how the complexity of athletes' cognitive skills can be measured and evaluated in terms of the higher-order structure, rather than the specific content of these representations. Our findings suggests that the skill to perceive game information—the players, the ongoing actions, etc.—in a more complex way, is characteristic for players with higher expertise levels. This suggestion fits with Fischer's (1980) notion that cognitive skills become more complex over the course of human (cognitive) development.

Chapter 3

In Chapter 3 we shifted our focus from a task that targeted cognitive skills to a task in which athletes actually had to perform a sports task. More specifically, we examined the temporal structure of variation in ergometer rowing performance, in order to draw inferences about the complexity of the underlying dynamic (motor) organization. The central limit theorem implies that when a large amount of measures are independently collected in a sample, and each of these measures consists of the sum of independent components, we would observe a normal distribution of these measured values (see Kello et al., 2010). In time series of actual task performance, this would mean that successive measurements are independent of previous measurements, that is, the temporal structure of variation would consist of random fluctuations around some mean value (i.e., white noise). However, we assumed that sport performance emerges from complexity, that is, rather than being determined by independent component effects, it emerges from the ongoing interactions between components across multiple time scales throughout the system. Such a complex dynamic organization would typically result in a more structured pattern of variation (i.e., pink noise) (e.g., Kello et al., 2010; Van Orden et al., 2003).

In order to test our assumption, we asked rowers to perform 550 strokes at their preferred rowing rhythm. Then, we examined the temporal structures of variation of the rowers' force peak intervals between stroke 18 and 530, in order to assure a sufficiently long time series to analyze. The structure in the time series was assessed based on a specific nonlinear time series technique: Detrended fluctuation analysis (DFA; Peng et al., 1993). As expected, for each rower the temporal structure deviated from white noise, and was close to pink noise. In addition, time series of rowers who were members of a first-year's team that was ranked among the best 16.67% nationally, revealed more pink noise than the time series of rowers who were members of a team ranked below-average (i.e., ranked between 50% and 67% nationally).

Taken together, the findings of Chapter 3 make it likely that motor performance in sport, specifically ergometer rowing, emerges from complexity. Indeed, pink noise in human behavior is assumed to be an expression of self-organizing system-components across multiple time scales, rather than the activation of components operating independently, or in a serial manner (e.g., Diniz et al., 2011; Gilden, 2001; Van Orden et al., 2003; Wijnants, 2014). In addition, more prominent patterns of pink noise were associated with higher rowing expertise in terms of recent team-results in (on-water) rowing competitions. The complexity of the dynamic organization underlying the generation of rowing strokes may thus be a reflection of rowing expertise, or more specifically of rowers' ability to continuously and functionally adapt their behavior to satisfy task constraints (see Seifert et al., 2013).

Chapter 4

The previous chapters provided insights into the (measurement of) complexity in situations in which we aimed to keep perturbing, outside influences to the minimum. These studies revealed that complexity at the level of cognitive skills, as well as the entire motor system underlying sport performance, is likely related to athletes' expertise levels. In Chapter 4, we shifted the focus to a complex phenomenon—*Psychological momentum* (PM)—, which is observed in various achievement contexts in which people are striving for specific goals. Positive and negative PM can emerge through interactions among a variety of precipitating events (e.g., scoring, referee decision, crowd behaviors, opponent behavior, etc., see Taylor & Demick, 1994), provided that they give rise to the perception that one is progressing or regressing in relation to a desired goal or outcome (Gernigon et al., 2010). In order to obtain the first insights into the emergence of positive and negative PM in teams, we studied the evolvement of a few collective psychological and behavioral variables (i.e., collective efficacy, task cohesion, exerted efforts, and interpersonal coordination). We did so by directly manipulating the position (progress or regress) in relation to the team goal, in order to examine how PM moves from its positive to its negative state, and the other way around. This strategy is in accordance with the guidelines defined by the HKB method (Haken et al., 1985).

In our study we made pairs of rowers, who formed a team. We placed them in a performance context (i.e., ergometer competition), and provided them with a clear goal to pursue: Beating the opponent by taking an 8-second lead. In the negative momentum race, we let the team take a lead of 6 seconds at the start, after which the team gradually moved toward a lag of 6 seconds. This scenario was the exact opposite in the positive momentum race. During the races we measured collective efficacy and task cohesion at fixed intervals of one minute, while we continuously measured the exerted efforts and interpersonal coordination. We found decreases in collective efficacy and task cohesion in the negative momentum scenario, which were relatively stronger than the increases in collective efficacy and task cohesion in the positive momentum scenario. It thus seems that, psychologically, teams converge more rapidly to a negative PM state than to a positive PM state. However, note that the pattern we found does not correspond to a typical hysteresis pattern, according to which we should have observed a resistance to change from positive to negative PM and vice versa (e.g., Bardy, Oullier, Bootsma, & Stoffregen, 2002; Hock, Kelso, & Schöner, 1993). We found asymmetrical dynamics, in which teams reacted more strongly to a scenario in which they start to lose seconds while they almost won. This is in line with Kahneman and Tversky's (1979) prospect theory according to which losses hurt more than gains feel good. Related to this, in our study exerted efforts decreased more rapidly in the negative momentum scenario than in the positive momentum scenario, while the interpersonal coordination was better in the positive momentum scenario.

In Chapter 4, we thus demonstrated an asymmetry between positive and negative PM in teams. Given our research setup, involving two exactly symmetrical (manipulated) scenarios, we may conclude that team PM is not only determined by some independent variable (e.g., the team's position in the race). If this were the case, we should have observed symmetrical linear increases and decreases in the variables under study during positive and negative momentum. The fact that we found significant differences between the scenarios suggests that team PM is a dynamical phenomenon demonstrating properties that are also found in complex dynamical systems, history-dependence in particular.

Chapter 5

While past studies on PM dynamics, including Chapter 4, have focused on psychological and behavioral changes within a race or match, athletes' PM may extend over a single match and develop over the course of a tournament or longer (Adler, 1981). The theory of complex dynamical systems postulates that processes taking place at different time scales are interconnected and mutually influence each other (e.g., Newell et al., 2001; Thelen & Smith, 1994). Given the evidence that PM is a complex and dynamical phenomenon (Briki et al., 2013; Briki, Den Hartigh et al., 2014; Gernigon et al., 2010; see also Chapter 4), we experimentally tested the property of interconnected time scales in PM processes.

The participants in this study were involved in a tournament, in which they competed in three (manipulated) races against a direct opponent on rowing ergometers. During the tournament, participants thought they could win a money prize by getting three points, which could be accomplished by winning three races (i.e., gaining 9 seconds on the opponent in each race). The races were manipulated, so that one group of participants lost the first two races (negative momentum condition), whereas the other group won the first two races (positive momentum condition). Before each subsequent race we assessed participants' perceptions of momentum and self-efficacy, to determine the influence of the previous race(s) on their long term PM development. Overall, on the long term, we found that perceptions of momentum and self-efficacy increased in the positive momentum condition and decreased in the negative momentum condition.

In the third race, the scenario was similar for all participants: From an almost victory—a lead of 6 seconds—they moved toward the defeat (i.e., losing 9 seconds on the opponent). To assess the PM dynamics, we measured the participants' perceptions of momentum and self-efficacy at fixed intervals of one minute, while we continuously collected their exerted efforts. We found that momentum and self-efficacy perceptions decreased less rapidly in the third race for participants who won the previous races (i.e., who developed positive long-term PM), than for participants who lost the previous races (i.e., who developed negative long-term PM). Furthermore, exerted efforts were higher for the participants in the positive momentum condition than for those in the negative momentum condition.

The finding that long-term PM was shaped by (short-term) races, and that the long-term PM seemed to shape the dynamics of short-term (within race) PM, supports the proposed interconnection between long- and short-term PM processes that is typical for complex dynamical systems. More specifically, PM dynamics within a task (i.e., race) seem to be constrained by the PM process on the long term, in a way that an athlete's state within a task converges less rapidly to negative PM when experiencing positive PM on a longer time scale.

Chapter 6

In the previous chapters we provided insights into complex processes taking place in relatively standardized situations, in which psychological and behavioral processes could directly be observed. Processes that take place across longer periods of time (e.g., years), and are distributed over a range of situational contexts, are more difficult to observe directly. One of the most debated long-term processes with regard to human performance, is the development of talent and excellence. So far, the debate has primarily focused on the nature of the underlying (causal) mechanisms of ultimate excellent performance, and its early indicators. While this discussion started in the 19th century (De Candolle, 1873; Galton, 1869), it is still ongoing (for hot recent debates on the roles of heritability and deliberate practice, see for instance Ackerman, 2014; Ericsson, 2014; Ericsson, 2013; Ericsson et al., 2013; Gagné, 2013; Hambrick et al., 2014; Plomin, Shakeshaft, McMillan, & TrzasKowski, 2014). Rather than focusing on specific components that may explain why some reach excellence, whereas others do not, Chapter 6 took a complexity approach. We aimed to construct a plausible model that predicts some typical properties of talent and excellence development across the domains of business, arts, science, and sports. Simonton (2001) has defined these properties as follows: (a) In different individuals a similar ability can emerge at different ages, (b) the underlying constituents of a particular ability can change during an individual's life span or career, (c) an individual's ability development over time can take a variety of forms, and (d) early indicators of later excellence are often absent. Another typical finding in the literature on talent and excellence is that the distribution of performance in terms of individuals' ultimate productivity is highly right-skewed across the population in virtually any performance domain (e.g., O'Boyle & Aguinis, 2012). To illustrate this, consider the following: In total, 404 professional tennis players have won *at least* one ATP tournament, 74 of them won only one tournament, whereas three exceptional players were able to win more than 80 tournaments: Federer, Lendl, and Connors (www.atpworldtour.com, accessed at 5 November 2014).

In order to discover the kind of model that reveals the typical properties of excellence, we simulated different kinds of models on a computer (cf. Nowak et al., 1990; 2000; Van Geert, 1991). We proceeded from the idea that excellence develops over time—from a beginner level up to the level at which excellent performance is demonstrated—and that a variety of factors are involved that influence, or are influenced by the changing ability level, such as practice, family support, coaching, etc. (e.g., Abbott et al., 2005; Phillips et al., 2010). In line with this idea, we simulated networks consisting of sparsely connected components. We found that the resulting trajectories corresponded to the typical developmental properties proposed in the literature (Simonton, 2001). Furthermore, the network model generated highly skewed productivity distributions across populations of performers, which has been consistently found across achievement domains (e.g., O'Boyle & Aguinis, 2012). While the network model produced highly plausible results in light of the current literature on talent and excellence development, the null-hypothesis model did not. More specifically, we were unable to detect the properties of talent and excellence when we simulated models in which abilities were normally distributed across the population, and were supported by the additive effects of all supporting factors.

Taken together, the results of our simulations suggest that excellence emerges from dynamic network structures. More broadly we showed that talent and excellence likely develop out of complexity—the ongoing interactions between sparsely connected components—rather than complicatedness—the additive influences of ability-related components.

7.3 How Do Our Findings Advance Insights in Human Performance Processes?

In this thesis, we assumed that performance-related states cannot be explained by linear relationships with specific underlying components, because such states are generated by a complex underlying process involving ongoing interactions between continuously changing components. This assumption had to be taken into account in our choice of methods, which should be able to draw inferences about the complexity of human performance processes.

As noted earlier, the processes we studied took place across different levels and time scales (from motor processes during a rowing ergometer session to person-environment interactions during excellence development). However, in all studies we found emergent patterns at a higher level, out of the underlying, dynamically interacting components at the lower level. The most comprehensive demonstration was provided in Chapter 6 on the development of excellence across a career. In this chapter we demonstrated higher-order patterns emerging out of specified (coupled) mathematical equations. Based on the network model we proposed, we could explain a) intra-individual trajectories from a beginner's level up to an excellent performance level, and b) inter-individual differences in the output, in terms of productivity, of excellent performers. Apart from Chapter 6, the findings of the other chapters also suggest that networks of interacting components are at work that a) form the basis for the ongoing representations that soccer players construct during game plays (Chapter 2), b) underlie the coordination of rowers' rowing strokes (Chapter 3), and c) move toward positive or negative PM during goal pursuit (Chapter 4 and 5); see Figure 21 for a schematic presentation. However, some elaboration may be needed about what our findings specifically mean in terms of the causality of human behavior, and performance processes in particular.

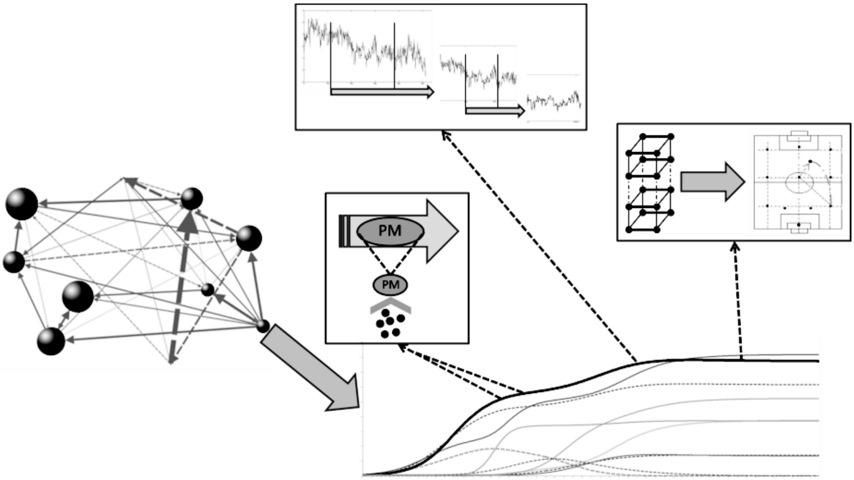


Figure 21. Schematic representation of the complexity at work in the different chapters. The numbers correspond to the numbers of the different chapters, and the processes take place across the time scale of excellence development to which the studies are connected.

7.4 What Do the Findings Suggest about Causality?

Given that none of the studies answered questions related to *which* components cause a particular psychological or performance state, one may conclude that none of the studies in this thesis identified the specific causal mechanisms underlying human performance. Yet, this does not entail that our studies, and the findings derived from them, hold no explanatory power. More specifically, based on the kinds of patterns we observed in the studies, we can provide plausible explanations on the kinds of processes (rather than the kinds of components) underlying the patterns (cf. Beek, Peper, & Stegeman, 1995). Below I will briefly clarify what our conclusions in terms of the underlying complex processes imply for the explanation of psychological and performance states.

For example, Chapter 3 focused on patterns of peak-to-peak interval series of rowing strokes. While debate has existed on the exact meaning of pink noise, or long-range correlations in time series (Diniz et al., 2011), researchers seem to have reached a general agreement that pink noise reflects the complexity of the system, in terms of the flexible and adaptive coordination between multiple components (Delignières & Marmelat, 2013; Delignières, Marmelat, & Torre, 2011). Because only knowing the output of the system, that is, the temporal structures of performance, could be considered as indirect evidence for the nature of the underlying system, Delignieres and colleagues recently performed computer simulations of different kinds of systems. The authors showed that pink noise time series are generated when distinct networks of components are simultaneously involved in the generation of performance (Delignières & Marmelat, 2013; Delignières et al., 2011). This interaction-dominant model is at odds with models that assume localized central pattern generators (e.g., Dimitrijevic, Gerasimenko, & Pinter, 1998). This pleads for a model that explains performance based on simultaneously interacting components, rather than a causal chain involving a control mechanism (e.g., the brain) that activates the actions to be performed.

In the Chapters 4 and 5 we proceeded from the assumption that PM is a dynamical and complex process, evidence for which has been provided in different recent studies (Briki, Den Hartigh, Bakker, & Gernigon, 2012; Briki et al., 2012; 2013; Briki, Den Hartigh et al., 2014; Gernigon et al., 2010). With this assumption in mind, the main focus in these studies was to examine *how* the dynamics of PM can be characterized, by scaling a control parameter that moves PM from its positive to its negative state. In other words, we focused on the properties of the patterns in PM-related variables when athletes undergo progress and regress in relation to their desired goal, which is in line with the HKB method (Haken et al., 1985). Our finding in Chapter 4 that team members' psychological and behavioral states converge more rapidly on a negative PM than a positive PM, suggests that positive PM is a weaker kind of equilibrium state than negative PM (i.e., negative PM would be a stronger attractor than positive

PM; see also Briki et al., 2013). Subsequently, Chapter 5 demonstrated a higher resistance to enter a negative PM when having experienced successes in previous competitions compared to having experienced losses in previous competitions. An additive model involving independent variables to explain PM at a certain moment is therefore unlikely to provide an explanation for the PM process. More specifically, the rate at which our thoughts, perceptions, and behaviors converge to a positive or negative PM state, is embedded in a performance history that takes place within a competition (Chapter 4), but also across multiple competition rounds (Chapter 5). To date, an actual dynamic systems (mathematical) model of PM has not been proposed, this remains a challenge for future research. One possibility might be to use the HKB-model, which allows the modeling of attractor dynamics and has already been successfully applied to the domains of postural coordination (Bardy et al., 2002), human locomotion (Diedrich & Warren, 1995), economics (Barnett & He, 1999), and speech categorization (Tuller, Case, Ding, & Kelso, 1994).

One chapter in which we explicitly modeled the emergence of performance processes, was chapter 6. Based on a coupled logistic growth equation, we simulated networks consisting of sparsely connected components, and we found that the patterns of ability growth corresponded to typical characteristics of talent and excellence development according to previous literature. In this study we also manipulated the network in a way that we removed the links between the components, thereby simulating a model in which ability development is influenced by the *sum of* —rather than the *interactions among*—the components. Because this latter model did not reveal patterns resembling characteristics of excellence according to the literature, our approach provides a new, and plausible notion of the process underlying talent and excellence development, based on a comparison of earlier literature and archival data with model simulation results.

Taken together, theoretically, findings of this dissertation do have explanatory power in terms of revealing the *kind of model* that can explain the emergence of psychological and performance states, and/or how psychological and performance patterns converge towards another pattern when being perturbed (i.e., from positive to negative PM and vice versa; see Chapters 4 and 5). Given that our findings suggest that the principle explanation of human performance processes may lie in the ongoing interactions between (causal) components, to which specific dynamical models apply (e.g., dynamic network models), the future research agenda can be adapted accordingly. In other words, instead of trying to fit additive linear models involving sets of determinants, we should (also) explore alternative models that account for the interaction-dominant processes in which the components are involved. I therefore recommend a three-pronged research strategy consisting of theory development, computer simulations, and empirical studies, each of which should inform the other two and lead to the improvement of the dynamic model explaining complex human performance processes across different levels and time scales (cf. McGrath et al., 2000).

7.5 Implications for Practice

Although this thesis was of a fundamental nature, and we have not investigated practical applications in this thesis, suggestions can be made that are specifically focused on positively altering psychological and performance patterns in terms of complexity or stability. For instance, with regard to Chapter 2, particularly expert soccer players seem to have the skill to construct complex representations of the actions taking place, which means that they are superior in extracting higher order *patterns* of information from the game plays. This is in line with Savelsbergh and colleagues, who stipulated that it is not so much a matter of gaze behavior per se (i.e., the kinds of information players look at, such as the ball or players on the field), but rather of *how* soccer players are able to use the information they perceive that distinguishes the elite adult players (Savelsbergh, Haans, Kooijman, & Van Kampen, 2010; Savelsbergh, Onrust, Rouwenhorst, & Van der Kamp, 2006). Although we have not examined the actual actions and decision making of the soccer players during an actual game, it is plausible that the skill to integrate information during game plays at higher complexity levels goes hand-in-hand with successful actions and decision making. For example, perceiving that a player ‘chooses position’ probably affords the action to chase or cover that player, whereas perceiving that same action as a player who ‘sprints’ may not afford such actions. In order to monitor or evaluate players’ ability to integrate the information on the field at high complexity levels (i.e., perceive patterns during ongoing game plays), coaches could apply the user-friendly coding system that we constructed (De Meij et al., 2012).

Chapter 3 showed that elite athletes display a pattern of variation suggesting that the motor system finds itself in a critical state allowing different modes of behavior (Van Orden et al., 2003). This is in line with the assumption that athletes should be flexible yet stable in their behaviors, in order to execute coordinated movements, while at the same time adjust in an ongoing athlete-environment interaction (e.g., Davids et al., 2003; Seifert et al., 2013). In the specific case of rowing, we may therefore cast doubt on a training practice in which athletes have to learn to repeatedly reproduce the exact same or ideal movement, and to minimize the variation from stroke-to-stroke. Following the results we found, another strategy could be considered, namely to let rowers practice at “the edge” or in a pink noise rhythm in order to stimulate complexity (cf. Chow et al., 2010; Marmelat, Torre, Beek, & Daffertshofer, 2014). Marmelat et al. (2014) have recently provided gait training to participants, which consisted of walking in line with an auditory metronome. The authors varied the pattern of interval variation of the metronome and found that (only) a pink noise pattern of variation elicited a pink noise gait pattern. Hence, to improve (coordination in) cyclical performance, which includes rowing, training according to a pink noise pattern could be a potential strategy.

If we take the above-mentioned idea one step further, we might speculate that adaptive behavior could be facilitated when coaches help athletes to explore the meta-stable regions of their performance landscape (e.g., Chow et al., 2011). In order to do so, rather than prescribing an athlete to practice the same movements repeatedly, a coach could place an athlete in a situation in which different (creative) performance solutions are available. For instance, Hristovski, Davids, Araújo, and Button (2006) showed that boxers were able to perform a diversity of actions (hooks, jabs, uppercuts) when they were at a certain (medium) distance from their target, thereby minimizing “mode-locked” behaviors and maximizing the possibility to learn different action patterns. Taken together, in order to stimulate the coordinated, yet flexible behaviors that elite athletes should develop, and which are typical for complex dynamic systems, practitioners such as coaches could attempt to introduce adaptive noise (i.e., functional variability) in the practice regimen (Chow et al., 2011).

Regarding PM (Chapters 4 and 5), practical implications could be focused on the (in)stability of PM. Findings from different studies, including Chapter 4, suggest that negative PM is triggered relatively easy compared to positive PM (Briki, Den Hartigh, Hauw et al., 2012; Briki et al., 2013; Gernigon et al., 2010). Strategies or interventions should thus attempt to improve the stability of a positive PM pattern in order to delay the emergence of negative PM. One strategy that can be applied within a sports match is to ask for a time out when one starts moving away from the victory. This time out may interrupt the formation of a (strong) negative PM attractor and provide the time and opportunity to recover a positive state (cf. Briki, Doron et al., 2014). Another strategy within and outside sports may be to endorse Mastery-approach (MAp) goals, that is, aiming to do better than before, or performing a task well (Elliot & Church, 1997; Van Yperen, 2003). A recent qualitative study on PM showed that MAp goal endorsement helped athletes to maintain positive PM, but also to overcome negative PM during a table tennis match or swimming race (Briki, Den Hartigh, Hauw et al., 2012). This is in line with general findings across sports, business, and education that MAp goals promote self-regulation, the maintenance of efforts, and the immersion in task (e.g., Elliot & Church, 1997; Elliot & McGregor, 2001; Van Yperen, 2006; Van Yperen, Blaga, & Postmes, 2014, in press).

Finally, considering talent and excellence development, the practical implications should focus on the structure of the individual ability networks rather than the components that generally relate to excellence across the population[6]. More specifically, the potential interactions between the components should be a principal focus of attention, which means that the probability of establishing positive feedback-loops between various ability-supporting components should be enhanced. This could be attained if the ‘supporters’ of talent in the child’s environment (coach, family, teacher) recognize their role as being (just) one component in the network, and if they stimulate ‘complexity’ rather than a mono-disciplinary life-style and/or training practice. This means that a coach or teacher, but also parents, should be sensitive

[6] According to recent advances in network science, specific components (driver nodes) may guide the dynamics of the network. Importantly, in these cases the controlling influence of driver nodes is embedded in, and dependent on, the structure of the dynamic network (Liu, Slotine, & Barabási, 2011). A discussion of the potential role of driver nodes in an individual’s ability-network is beyond the scope of this dissertation, but can be a fruitful avenue for future research.

to the child and its environment (e.g., the enthusiasm, engagement in school or sports) that signal supportive or competing influences for excellence to develop. In other words, the coach or teacher should be adaptive, because he or she is situated in an idiosyncratic and changing network that is typical for a particular athlete, artist, or scientist, and which involves mutual interactions between components.

The positive consequences of establishing a complex and rich ability network can be twofold. First, a network involving multiple (sparsely) coupled components may increase resilience. Although this speculation was not tested as such in Chapter 6, it follows from recent advances in network sciences that the higher the degree of a node, the less responsive it is to perturbations, or to changes in other nodes to which it is connected (Barzel & Barabási, 2013). Indirect support for this idea is also provided in earlier literature, showing that psychological and environmental variables, such as goal commitment, coping skills, parental support, and adequate coaching, influence the development of excellence, and more specifically that parental support may act as a buffer to alleviate performance-related stress and deal with setbacks (e.g., Baker et al., 2003; Côté, 1999; Van Yperen, 1995a, 1998, 2009). A second argument is that excellence development may generally benefit from hobbies and interests outside the performance domain in which the performer wants to excel (Simonton, 2014). Examples of this idea include Galileo, who was fascinated by arts, literature, and music (Simonton, 2012), the finding that the most creative scientists pursue a large number of different (and loosely-related) projects (Gruber, 1989), and the proposition that children would benefit from sampling different sports and activities in order to facilitate excellence development in a specific sports domain at a later age (e.g., Abbott & Collins, 2004; Baker, 2003; Côté, Lidor, & Hackfort, 2009).

Finally, note that the above-mentioned propositions with regard to the development of excellence do not correspond to the idea that, primarily, deliberate practice should be accumulated in order to develop excellence (Ericsson et al., 1993). To date, the talent development policies of some countries (e.g., the China policy on developing gymnastics talent) still proceed from the idea that children’s ability development benefits most from stimulating the ability-development with much deliberate practice in environments that are deprived from many other components. That is, in these programs children are often (temporarily) cut from their family and friends, and there seems to be less care for the general psychological well-being of the child. Because the network model assumes that excellence can be "fed" by multiplicative relationships between a variety of components, we may cast doubt on a policy that emphasizes just one, or very few, links (e.g., only between ability, coach, and practice). However, new empirical studies and simulation studies should be conducted to more explicitly test the consequences of different kinds of network structures with regard to the development of excellence.

7.6 Concluding Remarks

"Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). This quote reflects Tobler's first law of geography, which entails that at the level of the globe, patterns of change are a function of (in)directly interrelated components, such as climate, population, land use, industries, which are in an ongoing interaction across multiple scales of time and space. Tobler's (1970) law also seems to apply to the relatively small scale of human performance. In this thesis we found that (a) ongoing representations formed by soccer players involve the structuring of directly observable components (e.g., the player with the ball), but also more distant and not directly observable components, in particular for expert soccer players; (b) components of the human motor system, spanning multiple scales (e.g., processes at the levels of cells, muscles, limbs), are in continuous interaction, and the interactions are better coordinated for elite rowers; (c) in a performance context PM is characterized by ongoing psychological and behavioral changes that are shaped by the history of events within and across performances (i.e., competitions); and (d) excellence develops over a career or life span through ongoing interactions between proximal (directly connected) and more distal (indirectly connected) components pertaining to different personal and environmental factors.

The idea that everything is related to everything else fits with the premise we started from, namely, that the principal mechanism to explain human performance processes lies in the underlying complexity. In this thesis we have shown that complex performance processes, involving ongoing interactions between multiple components, can be captured by applying a complex dynamical systems approach, ranging from empirical studies zooming in on temporal processes during specific sport tasks to life-span simulation and archival research across sports, arts, business, and science. In all studies we came to the conclusion that the patterns we found are likely generated by a set (or network) of interacting components, which sheds a new light on the way we should explain performance-related processes in real-time and on longer time scales (e.g., during excellence development over years). Therefore, I hope that the methods and results derived from this thesis open up new lines of research and ultimately lead to practical interventions focused on developing and adjusting the dynamical structures that shape human performance.

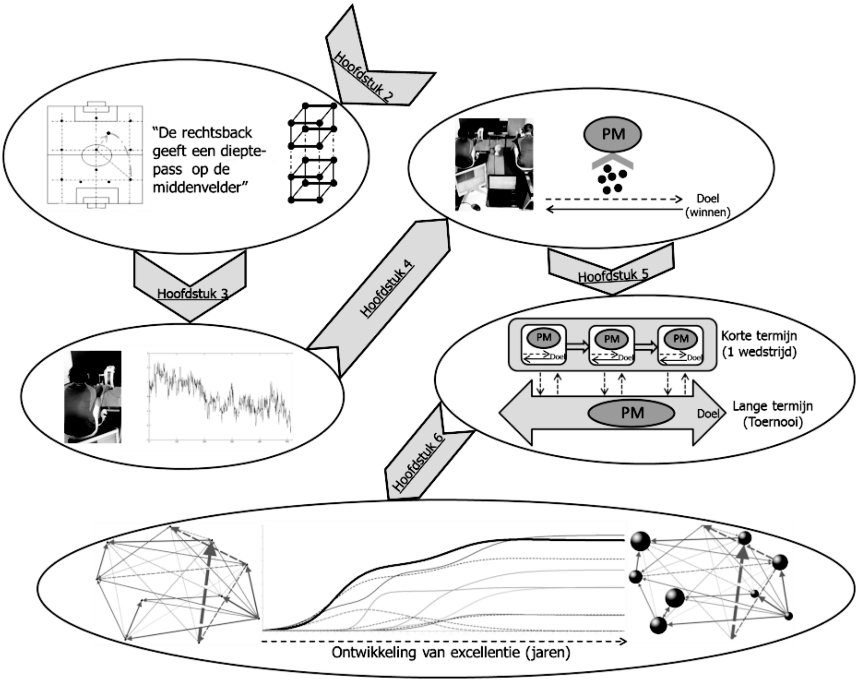
Chapter 8: Nederlandse Samenvatting (Summary in Dutch)

8.1 Overzicht

Het leveren van prestaties wordt door vele factoren beïnvloed, die op hun beurt kunnen veranderen over tijd en elkaar over en weer beïnvloeden. Zo hebben sporters tijdens een wedstrijd allerlei gedachten en gevoelens (bv. zelfvertrouwen), die in interactie met omgevingsfactoren (bv. het niveau van de tegenstander, beslissingen van de scheidsrechter) tot prestatieveranderingen kunnen leiden, wat vervolgens weer kan leiden tot veranderingen in de gedachten en gevoelens van de sporter, etcetera. Over de tijdspanne van een carriere is een zelfde soort proces te zien. Denk aan een kind dat tennistalent lijkt te hebben. De ouders zullen het kind waarschijnlijk stimuleren en trainingen betalen. Door het trainen nemen de tennisvaardigheden van het kind toe en daarmee bijvoorbeeld ook zijn of haar motivatie om door te gaan. Dit kan vervolgens weer invloed hebben op de ondersteuning die het kind krijgt van de ouders. Prestatieprocessen zijn dus complex en spelen zich voortdurend af op verschillende tijdschalen (korte en lange termijn).

De gangbare benadering in de sociale en sportwetenschappen is om de verklaring van bepaalde toestanden, zoals psychologische toestanden of prestatie uitkomsten, te reduceren tot een aantal specifieke, factoren. Deze benadering gaat er dus impliciet vanuit dat psychologische en prestatietoestanden veroorzaakt worden door een optelsom van componenten, waarvan de bijdragen los van elkaar bestudeerd kunnen worden. Bijvoorbeeld, in vergelijking met niet-topsporters, heeft de populatie topsporters in het algemeen een betere lichamelijk fitheid én betere begeleiding én meer natuurlijke aanleg én betere motorische vaardigheden én meer tactisch inzicht is én meer trainingsuren gemaakt (Van Rossum & Gagné, 1994). Op basis van ons idee dat psychologische en prestatietoestanden waarschijnlijk emergent zijn, stellen we in dit proefschrift echter ander soort modellen en technieken voor. In algemene zin wordt met emergentie bedoeld dat orderlijke en adaptieve toestanden ontstaan vanuit voortdurende interacties tussen verschillende componenten over tijd, waardoor de (veranderlijke) toestanden niet direct terug te leiden zijn tot de bijdragen van de individuele componenten (Kelso, 1995; Nowak & Vallacher, 1998; Van Geert, 1994). In dit proefschrift hebben we daarom een complexiteitsbenadering toegepast, die uitgaat van de aanname dat toestanden zich niet laten verklaren uit geisoleerde componenten, maar zich ontwikkelen en aanpassen vanuit continue *interacties tussen* componenten (Ottino, 2004).

De methoden die we hebben gebruikt zijn relatief onbekend binnen de sociale- en sportwetenschappen, maar zijn binnen andere domeinen (bv. natuurkunde, economie, biologie) met succes gebruikt om de complexiteit en dynamiek van processen in kaart te brengen. Door methoden en technieken van de complexiteitsbenadering toe te passen, trachtten de studies in dit proefschrift nieuwe inzichten te geven in de processen die ten grondslag liggen aan verschillende psychologische toestanden en prestaties op verschillende niveaus en tijdschalen (zie Tabel 1 in de Introductie en Figuur 22), zoals (a) de (cognitieve) representaties die voetballers continue vormen tijdens fragmenten van voetbalwedstrijden, (b) de bewegingen van roeiers tijdens het ergometer roeien, (c) veranderingen in psychologische en prestatievariabelen tijdens positief en negatief momentum en (d) de ontwikkeling van excellente prestaties (talentontwikkeling). De afzonderlijke studies en bevindingen worden hieronder uitvoeriger besproken.



Figuur 22. Overzicht van het proefschrift. De verschillende hoofdstukken behandelen complexiteit op verschillende niveaus en tijdschalen: Hoofdstuk 2 richt zich op de complexiteit van cognitieve vaardigheden op basis van verbalisaties tijdens voetbal spelfragmenten; Hoofdstuk 3 belicht de complexiteit van de dynamische organisatie die ten grondslag ligt aan roeislagen gedurende een ergometer sessie; Hoofdstuk 4 richt zich op de ontwikkeling van een complex fenomeen—psychologisch momentum (PM)—binnen een wedstrijd op roei-ergometers; Hoofdstuk 5 test de connectie tussen PM binnen een wedstrijd en PM over verschillende wedstrijden; Hoofdstuk 6 verklaart de lange termijn ontwikkeling van excellente prestaties vanuit een complex, dynamisch model.

Hoofdstuk 2

In hoofdstuk 2 hebben we de complexiteit onderzocht van de representaties die voetballers vormen tijdens het kijken naar voetbalfragmenten. Deze representaties vormen zich door componenten te integreren, zoals de posities en bewegingen van de spelers op het veld (Helsen & Starkes, 2000), of de acties die uitgevoerd worden door de spelers, zoals de acties van de speler in balbezit, verdedigende acties, etcetera (Roca et al., 2011). Eerder onderzoek heeft al aangetoond dat experts (professionele voetballers) meer componenten lijken te zien, zoals de speler met de bal en de (vrije) ruimtes rondom de speler. Het is echter nog onbekend hoe voetballers verschillende componenten aan elkaar koppelen, wat de basis vormt voor het spelinzicht (de representaties) gedurende de wedstrijd, of fragmenten daarvan (Roca et al., 2011). In deze empirische studie hebben we een codeerboek ontwikkeld gebaseerd op Skill Theory (Fischer, 1980; Fischer & Bidell, 2006). Skill Theory veronderstelt dat complexere inzichten of representaties gebaseerd zijn op het koppelen van simpele componenten (bv. “de speler schiet de bal naar de ander”) tot complexere structuren (bv. “de linksback geeft een steekpass op de nummer 10”; hiervoor is inzicht vereist in de posities van de spelers op het veld, de posities van de medespeler en het soort pass dat gegeven wordt). De complexiteit van de representaties, zoals deze voorturend worden gevormd tijdens het kijken naar spelfragmenten, hebben we op basis van ons codeerboek onderzocht bij experts (professionele voetballers), bijna-experts (hoofdklasse spelers) en niet-experts (spelers in een lagere amateurklasse).

De resultaten lieten zien dat spelers met meer expertise representaties vormen op een hoger complexiteitsniveau. Daarnaast vonden we dat spelers met meer expertise relatief vaker een hoger complexiteitsniveau scoorden op acties *buiten* de speler in balbezit (loopacties en vededigende acties). Samenvattend illustreert dit hoofdstuk hoe de cognitieve vaardigheden van voetballers gemeten kunnen worden in termen van complexiteit; het integreren van interacties tussen verschillende componenten bij het vormen van (voortdurende) representaties.

Hoofdstuk 3

Terwijl hoofdstuk 2 zich vooral richtte op cognitieve vaardigheden tijdens het kijken naar sportfragmenten, keken we in hoofdstuk 3 naar de complexiteit van de motorische organisatie die ten grondslag ligt aan de daadwerkelijke uitvoering van een sporttaak. Specifiek hebben we in dit hoofdstuk de variatie over tijd in de roeislagen van roeiers tijdens een ergometer sessie onderzocht. Volgens de literatuur geven temporele structuren van variatie namelijk inzicht in de onderliggende dynamische organisatie (Van Orden et al., 2003). Als opeenvolgende metingen onafhankelijk zijn van voorafgaande metingen, zullen er willekeurige variaties te zien zijn van meting tot meting (‘white noise’). Een dergelijk patroon zal naar voren komen als iedere volgende roeislag opnieuw wordt aangestuurd door opeenvolgende processen (denk aan een motorisch programma, een opeenvolging van spiercommando’s; Keele, 1968). Zoals eerder aangegeven vertrokken we in dit proefschrift echter vanuit het standpunt dat prestaties (in dit geval de roeislagen) ontstaan vanuit complexiteit, wat betekent dat de componenten voortdurend met elkaar in interactie zijn op verschillende tijdschalen. Een dergelijk proces laat zich uitdrukken in een meer gestructureerd patroon van variatie, dat ‘pink noise’ wordt genoemd (Kello et al., 2010; Van Orden et al., 2003). Wanneer een serie metingen pink noise laat zien, zijn de metingen *lange-termijn afhankelijk* (Diniz et al., 2011). In deze studie zou dat bijvoorbeeld betekenen dat de 400ste roeislag *niet* onafhankelijk is van de 300ste slag, de 100ste slag, etcetera.

Om deze aanname te testen hebben we roeiers van twee roeiploegen gevraagd om 550 roeslagen te maken in hun voorkeursritme. Vervolgens hebben we de variatie in de tijdsintervallen tussen de krachtpieken van de roeislagen genomen als analysemaat en hierop een nonlineaire tijdserie-analyse toegepast (detrended fluctuation analysis; Peng et al., 1993). De resultaten lieten zien dat de temporele structuur van de variatie voor iedere deelnemer significant afwijkt van ‘white noise’ en dat met name de roeiers in de beste roeiploeg een patroon hebben dat dichtbij ‘pink noise’ ligt. Deze resultaten ondersteunen het idee dat er een complexe motorische organisatie ten grondslag ligt aan de uitvoering van cyclische sportbewegingen (i.e., roeislagen). Omdat de tijdseries van de roeiers in de betere roeiploeg daarnaast meer ‘pink noise’ lieten zien, zou de complexiteit van de motorische organisatie een indicator kunnen zijn van de expertise van een roeier. Dit zal echter verder onderzocht moeten worden.

Hoofdstuk 4

In de vorige hoofdstukken onderzochten we complexiteit in situaties waarin de onderzoeksdeelnemers (sporters) zo min mogelijk werden beïnvloed door andere factoren tijdens de metingen. Binnen een prestatiecontext (op school, in een organisatie, op het sportveld) streven mensen echter vaak specifieke doelen na en de voortgang kan door allerlei factoren beïnvloed worden, zoals het scoren van een punt in een sportwedstrijd, beslissingen van de scheidsrechter, het publiek, de acties van de tegenstander, etcetera. Wanneer een persoon of team ziet dat het doel (bv. het winnen van de wedstrijd) dichterbij komt, of juist verder weg raakt, kan de persoon of het team in een soort positieve of negatieve spiraal komen, dit wordt positief of negatief psychologisch momentum (PM) genoemd (Briki, Den Hartigh, Hauw et al., 2012). In Hoofdstuk 4 hebben we getracht om de eerste inzichten te verschaffen in hoe de dynamiek van team PM er uitziet, op basis van een methode om complexe dynamische processen experimenteel te onderzoeken (de HKB-methode; Haken et al., 1985).

In deze studie namen teams, bestaande uit twee roeiers, het op tegen een virtuele tegenstander in een ergometer race. Tijdens de race maten we voortdurend de inspanningen van de roeiers—de kracht van de roeislagen—en de coordinatie tussen de roeislagen van de roeiers. Om inzicht te krijgen in de dynamiek van belangrijke psychologische teamvariabelen, verschenen er tijdens de race iedere minuut twee vragen op het scherm: Een vraag over taakcohesie en een vraag over ‘collective efficacy’. Taakcohesie is de mate waarin teamleden samenwerken om een specifiek doel te bereiken (Carron & Hausenblas, 1998), collective efficacy is de mate waarin teamleden vertrouwen hebben in hun vaardigheden om de teamtaak succesvol te uit te voeren. De teams namen deel aan twee races en voorafgaand aan iedere race gaven we aan dat het doel was om een voorsprong van 8 seconden te pakken op de tegenstander. De races waren echter vooraf geprogrammeerd. In een positief momentum race kwamen de teams langzaam terug van een bijna nederlaag (een achterstand van 6 seconden) tot het punt dat zij vlakbij het doel waren (een voorsprong van 6 seconden). In de andere race, een negatief momentum race, was het scenario exact het tegenovergestelde.

De variabelen taakcohesie en collective efficacy lieten neerwaartse veranderingen zien in de negatief momentum race, die sterker waren dan de opwaartse veranderingen in de positief momentum race. Het lijkt erop dat teams sneller een negatieve PM ervaring ontwikkelen dan een positieve PM ervaring. Dit werd bevestigd door de uitkomst dat de inspanningen van de teams sneller afnamen in de negatief momentum race en dat de coördinatie tussen de roeiers beter was in de positief momentum race. De bevinding dat de exact symmetrische race scenarios verschillende resultaten opleverden, suggereert dat PM een dynamisch fenomeen is dat typische eigenschappen laat zien—met name tijdsafhankelijkheid—die kenmerkend zijn voor complexe dynamische systemen. We vonden namelijk dat de psychologische toestanden en prestaties van de teams niet alleen door de positie in de race werden gevormd, maar door de positie in de race in functie van de recente geschiedenis (winnen of verliezen van seconden eerder in de race).

Hoofdstuk 5

Tot nu toe heeft onderzoek naar PM vooral gekeken naar psychologische en (soms) prestatieveranderingen binnen sportwedstrijden (zie Hoofdstuk 4). PM kan zich echter ook ontwikkelen over wedstrijden heen, bijvoorbeeld tijdens een toernooi of gedurende een seizoen (Adler, 1981). Volgens de theorie van dynamische complexe systemen, zijn processen die zich op korte termijn afspelen gekoppeld aan processen die zich op langere termijn afspelen (Newell et al., 2001). Omdat wij veronderstellen dat PM een complex dynamisch fenomeen is, hebben we in dit hoofdstuk getest hoe lange termijn PM zich ontwikkelt op basis van "losse" wedstrijden en hoe de dynamiek van PM gedurende een wedstrijd gevormd wordt door het opgebouwde lange termijn PM.

Voor deze studie hadden we sporters gevraagd om deel te nemen aan een toernooi op roei-ergometers. We vertelden de deelnemers dat zij geld konden winnen wanneer zij drie punten haalden, die ze konden verdienen door middel van het winnen van wedstrijdraces. De winnaar van een race was diegene die als eerste een voorsprong van 9 seconden pakte op de tegenstander. Van tevoren hadden we de races echter al geprogrammeerd en de deelnemers werden verdeeld over twee groepen: Eén groep won de eerste twee races (positief momentum groep) en de andere groep verloor de eerste twee races (negatief momentum groep). Om de lange termijn PM ervaring te meten, gaven we de deelnemers voorafgaand aan de tweede en derde race een korte vragenlijst met daarin vragen gerelateerd aan PM: De perceptie van momentum en self-efficacy. Over de races heen vonden we dat de groep die de eerste twee races won positief PM ontwikkelde, terwijl de groep die de races verloor negatief PM ontwikkelde.

In de derde race van het toernooi was het raceverloop gemanipuleerd volgens de richtlijnen van de HKB methode (Haken et al., 1985). In deze race gingen *alle* deelnemers van een bijna overwinning (een voorsprong van 6 seconden) langzaam op de nederlaag af (een achterstand van 9 seconden). Om de dynamiek van PM in de race te onderzoeken, beantwoordden de deelnemers iedere minuut tijdens de race een vraag gericht op hun perceptie van momentum in deze race en hun self-efficacy. Daarnaast maten we voortdurend hun inspanningen (i.e., de kracht van de roeislagen). De resultaten lieten zien dat de momentumperceptie en self-efficacy sneller afnamen voor de groep die de eerste twee wedstrijden had verloren (de groep die negatief PM had ontwikkeld over de wedstrijden heen) dan voor de groep die de eerste twee wedstrijden had gewonnen (de groep die positief PM had ontwikkeld over de wedstrijden heen). Daarnaast lagen de inspanningen tijdens de race hoger voor de groep die positief PM had ontwikkeld gedurende het toernooi.

De bevindingen samen geven een dieper inzicht in de tijdsafhankelijkheid van PM dan eerdere studies (Briki et al., 2013; Gernigon et al., 2010; Hoofdstuk 4), door te laten zien dat korte termijn PM processen (binnen een race) gekoppeld zijn aan langere termijn PM processen (over races heen). Specifieker, een sporter ontwikkelt tijdens een wedstrijd minder snel negatief PM als deze een postitief PM heeft ontwikkeld op de lange termijn (i.e., over wedstrijden heen).

Hoofdstuk 6

In de voorgaande hoofdstukken lag de nadruk op het onderzoeken van complexe dynamische processen op relatief korte tijdschalen (tijdens prestaties zelf en over enkele wedstrijden heen). Dit soort processen kan vaak onderzocht worden binnen de specifieke omgeving waarin de prestaties plaatsvinden. Bij processen die een langere tijd in beslag nemen en die verspreid zijn over verschillende omgevingen is dit echter lastig. Denk hierbij aan talentontwikkeling, of de ontwikkeling van excellente prestaties. Onderzoekers en filosofen hebben zich bijna 150 jaar beziggehouden met de vraag welke factoren ten grondslag liggen aan de ontwikkeling van excellentie. Terwijl deze discussie nog steeds aan de gang is (Ericsson, 2013; Ericsson et al., 2013; Gagné, 2013), kozen we in hoofdstuk 6 voor een andere aanpak. Zonder direct in te gaan op specifieke voorspellende factoren, was het doel van dit hoofdstuk om te onderzoeken vanuit welk soort model excellentie zich ontwikkelt. We hebben modellen gesimuleerd op een computer, op basis waarvan individuele talentontwikkelingstrajecten verklaard kunnen worden, maar ook interindividuele verschillen met betrekking tot domein-specifieke verdelingen van excellente prestaties.

We startten vanuit het idee dat excellentie zich ontwikkelt over tijd van een beginnersniveau tot een uiteindelijk (excellent) niveau. Daarnaast gingen we er in ons model vanuit dat verschillende factoren een rol spelen, die veranderen over tijd en elkaar direct en indirect kunnen beïnvloeden, denk bijvoorbeeld aan de tennisvaardigheid van een kind, training, ondersteuning van de ouders, steun van de coach, etcetera (Abbott et al., 2005; Baker et al., 2003; Phillips et al., 2010). We hebben daarom modellen gesimuleerd in de vorm van netwerken, die bestaan uit 10 componenten, waarbij ieder component direct of indirect gekoppeld is aan een aantal andere componenten (bv. de coach beïnvloedt de vaardigheid van een kind, die vervolgens de ondersteuning van de ouders beïnvloedt, de ondersteuning van de ouders beïnvloedt de vaardigheid ook weer positief, etcetera).

De modelsimulaties genereerden een aantal patronen die kenmerkend zijn voor de ontwikkeling van talent en excellentie volgens eerdere literatuur (zie Simonton, 2001), zoals (a) een bepaald talent kan op verschillende leeftijden naar boven komen bij verschillende individuen, (b) de onderliggende componenten die talentontwikkeling beïnvloeden kunnen veranderen over tijd, (c) de ontwikkelingstrajecten kunnen verschillende vormen aannemen voor verschillende individuen en (d) vroege indicatoren van latere excellente vaardigheden zijn vaak afwezig. Daarnaast genereerden de modelsimulaties rechtsscheve verdelingen van uiteindelijke prestatie output, die in vrijwel ieder prestatiedomein voorkomen (O'Boyle & Aguinis, 2012). Om dit laatste punt te verduidelijken, het volgende voorbeeld illustreert een dergelijke rechtsscheve verdeling van prestatie-output in sport. In totaal hebben 404 tennissers hebben ooit een ATP toernooi gewonnen. Van deze spelers hebben 74 spelers één toernooi gewonnen en slechts drie uitzonderlijk goede spelers hebben meer dan 80 toernooien gewonnen: Federer, Lendl en Connors (www.atpworldtour.com, geraadpleegd op 5 november 2014).

De resultaten van de simulaties maken het zeer aannemelijk dat de ontwikkeling van excellentie gekenmerkt kan worden als een complex dynamisch proces. Met andere woorden, excellentie ontwikkelt zich waarschijnlijk vanuit dynamische netwerkstructuren. Om het model concreet te kunnen gebruiken voor bijvoorbeeld de praktijk, zal toekomstig onderzoek zich meer moeten verdiepen in de eigenschappen van bepaalde individuele netwerkstructuren. Hierbij kan gedacht worden aan welk soort talentnetwerk het beste “klappen” kan opvangen, hoe verschillende netwerken reageren op bepaalde veranderingen, zoals een andere school of een andere coach, etcetera.

8.2 Conclusie

Dit proefschrift heeft laten zien hoe prestatie-gerelateerde processen, waarbij meerdere componenten met elkaar in interactie zijn en veranderen over tijd, onderzocht en begrepen kunnen worden door een complexiteitsbenadering toe te passen. We hebben gebruik gemaakt van Skill Theory (hoofdstuk 2), nonlineaire tijdserie-technieken (hoofdstuk 3), de HKB methode (hoofdstukken 4 en 5) en computersimulaties (hoofdstuk 6). De resultaten van de verschillende studies lieten zien dat (a) voetballers met meer expertise complexere representaties vormen terwijl zij naar spelfragmenten kijken, (b) er een complexe motorische organisatie ten grondslag lijkt te liggen aan de uitvoering van roeislagen, met name voor de betere roeiers, (c) PM gekenmerkt wordt door psychologische- en prestatieveranderingen die tijdsafhankelijk zijn en (d) excellente prestaties waarschijnlijk ontwikkelen vanuit voortdurende interacties tussen direct en indirect gekoppelde componenten.

De resultaten van dit proefschrift tonen aan dat een complexiteitsbenadering waardevolle technieken biedt om tot nieuwe inzichten te komen in *hoe*, *wanneer* en *waarom* bepaalde psychologische toestanden en prestaties veranderen. De uitgevoerde studies waren met name fundamenteel van aard, maar kunnen concrete handvatten bieden voor toekomstig onderzoek en praktische toepassingen. Relevant lijkt met name een focus op de interactie tussen componenten over tijd, of de structuur van het netwerk waarin de componenten actief zijn. Dit betekent dat het van belang is om te bekijken hoe op een positieve manier ingegrepen kan worden op de interacties of de eigenschappen van de structuren. Bijvoorbeeld, in hoofdstuk 3 suggereerden we dat er een complexere dynamische organisatie ten grondslag ligt aan de roeislagen van de betere roeiers, waardoor zij stabiel zijn in hun roeislag, maar tegelijk flexibel om zich aan te passen. Onderzocht kan worden of deze stabiele flexibiliteit getraind kan worden, bijvoorbeeld door roeislagen te oefenen volgens een ‘pink noise’ patroon met behulp van een metronoom (zie Marmelat et al., 2014). Een dergelijke strategie kan afgezet worden tegen een meer gangbare strategie, die vooral het ‘inslijpen’ van roeislagen benadrukt volgens vaste slagritmes.

In het geval van PM kan bekeken worden welke strategieën ervoor zorgen dat psychologische en prestatievariabelen minder snel convergeren naar een negatief PM patroon (Briki, Den Hartigh, Hauw et al., 2012). In dit geval kan gedacht worden aan het vragen van een time-out in een wedstrijd. Door een time-out krijgt kan het systeem (de PM toestand) de tijd krijgen om zich te ‘herorganiseren’ (cf. Briki, Doron et al., 2014).

Met betrekking tot de ontwikkeling van excellentie lijkt een belangrijk aandachtspunt om positieve koppelingen te introduceren of te versterken in het netwerk, om op die manier de ontwikkeling te stimuleren en een vangnet te hebben voor tegenslagen. Het belang van het vestigen van een optimale netwerkstructuur is bijvoorbeeld terug te zien in het werk van Van Yperen. Terwijl de meeste studies op het gebied van talentontwikkeling gericht waren op het belang van natuurlijke aanleg en training, heeft Van Yperen aangetoond dat ondersteuning van ouders en bepaalde psychologische componenten zoal doel commitment, een belangrijke rol spelen in de ontwikkeling van een sporter (Van Yperen, 1995a; 1998; 2009). In netwerktermen lijkt het van belang dat de vaardigheid van een sporter zich ontwikkelt in een rijk netwerk, waarbinnen de kans op positieve links tussen verschillende componenten wordt vergroot (voor een interessant praktijkvoorbeeld, zie Van Yperen, 1995b). Hiermee samenhangend is het aannemelijk dat rijke netwerken samengaan met een positieve ontwikkeling tijdens en na de sportcarrière (maar ook carrières in andere prestatiedomeinen), in vergelijking met opleidingen waarbinnen kinderen bijvoorbeeld in een internaat wonen, hard worden aangepakt en de voornaamste focus op slechts één component ligt: veel trainen.

Samenvattend heeft dit proefschrift verschillende toepassingen van een complexiteitsbenadering gedemonstreerd. Op basis van deze benadering zijn we tot nieuwe inzichten gekomen in de complexiteit en dynamiek van prestatieprocessen, zowel tijdens de uitvoering van (sport)taken als gedurende de langere termijn waarop talent zich ontwikkelt. Een volgende uitdaging is om de complexe en dynamische processen, die ten grondslag liggen aan psychologische- en prestatieprocessen, verder te specificeren en te vertalen naar concrete toepassingen voor de praktijk.

Chapter 9 : Résumé en Français (Summary in French)

9.1 Vue d’Ensemble

La performance est influencée par de nombreux facteurs qui évoluent au cours du temps et s’influencent mutuellement. Par ailleurs, en cours de performance, un athlète passe par de nombreux états psychologiques. La confiance en soi, par exemple, associée aux facteurs environnementaux tels que le niveau de l’adversaire ou les décisions des arbitres, peut induire des variations dans la performance de l’athlète, elles-mêmes pouvant déclencher l’irruption de pensées et de sentiments particuliers, et ainsi de suite. Tout au long d’une carrière, un processus similaire est observable. Prenons le cas d’un enfant semblant avoir des prédispositions pour le tennis. Les parents encourageront probablement leur enfant en lui offrant des entraînements. Ceux-ci engendreront des progrès en termes d’amélioration de ses compétences, laquelle nourrira une motivation supplémentaire et l’envie de continuer dans ce sport. À son tour, cette motivation, pourra influencer le soutien de ses parents. Les processus entraînant la performance sont donc complexes et constamment influencés par des paramètres agissant tant à court qu'à long terme.

L'approche traditionnelle en psychologie et sciences du sport consiste à réduire l'explication de l’occurrence de certains états, comme par exemple les conséquences psychologiques d’un succès, à un certain nombre de facteurs spécifiques et essentiellement indépendants. De ce fait, cette approche considère implicitement que les états psychologiques et les performance sont déterminés par une addition d’éléments dont les contributions peuvent être analysées indépendamment les unes des autres. Par exemple, l’appartenance à l’élite mondiale de certains athlètes de haut niveau est classiquement imputée à une meilleure forme physique, des meilleurs entraîneurs, davantage de talent naturel, des facultés motrices supérieures, une meilleure vision stratégique, ainsi qu’un plus gros volume d'entraînement, comparativement aux autres sportifs (Van Rossum & Gagné, 1994). D’autres modèles et approches, basés sur notre hypothèse que les états psychologiques et la performance sont probablement émergents, sont exposés dans cette thèse. De manière générale, l’émergence est décrite par des états adaptatifs organisés émergeant de l’interaction de plusieurs composants au cours du temps. Un état (changeant) ne peut donc être directement corrélé aux valeurs des composantes individuelles du système duquel il émerge (Kelso, 1995; Nowak & Vallacher, 1998; Van Geert, 1994). Par conséquent, une approche de la complexité est adoptée dans cette thèse, fondée sur la supposition qu'il est virtuellement impossible d'expliquer les différents états par des facteurs isolés, mais qu'ils évoluent et s'adaptent aux *interactions continues entre* différents éléments d'un système complexe (Ottino, 2004).

Certaines méthodes utilisées dans cette thèse sont relativement peu connues en psychologie, que celle-ci soit appliquée au sport ou non. Mais ces méthodes sont employées avec succès dans d'autres domaines, tels que la physique, l'économie ou la biologie, pour rendre compte de la complexité et de la dynamique des processus. En appliquant les méthodes et techniques de l'approche de la complexité, ce travail de recherche tente d'apporter de nouveaux éclairages aux phénomènes sous-jacents aux divers états psychologiques et de la performance, ce à différentes échelles temporelles (cf. tableau 1 et figure 22), tels que (a) les représentations (cognitives) que les footballeurs élaborent en continu lors de séquences de match, (b) les mouvements des rameurs sur ergomètre, (c) les changements des variables psychologiques et des performances lors de l'expérience d'un momentum positif (spirale ascendante) ou d'un momentum négatif (spirale descendante), et finalement, (d) le développement de la performance excellente (développement du talent). Les recherches spécifiques menées à ces fins ainsi que leurs résultats sont développés ci-dessous.

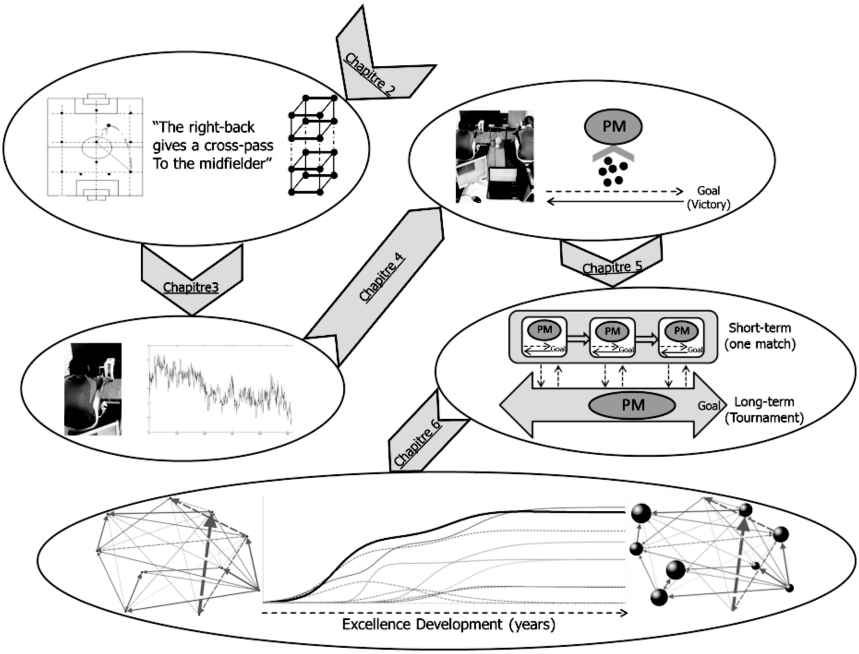


Figure 23. Vue d'ensemble de la thèse. Le chapitre 2 se concentre sur la complexité des capacités cognitives, telle que capturée via la verbalisation sur des extraits de vidéo de matches de football. Le chapitre 3 traite de la complexité de l'organisation dynamique de mouvements effectués par des rameurs lors d'une tâche d'aviron sur ergomètre. Le chapitre 4 est consacré à l'étude du développement d'un phénomène complexe—le momentum psychologique—lors d'une course d'aviron sur ergomètre. Le chapitre 5 teste la relation entre le momentum psychologique expérimenté lors d'une course et le momentum psychologique expérimenté sur plusieurs courses. Le chapitre 6 propose une explication du développement à long terme de la performance excellente basée sur un modèle dynamique et complexe.

Chapitre 2

Dans le chapitre 2, la complexité des représentations que les joueurs de football élaborent lors du visionnage d'extraits vidéo est étudiée. Ces représentations sont formées par intégration d'éléments tels que les positions et mouvements des joueurs sur le terrain (Helsen & Starkes, 2000) ou les actions réalisées par ceux-ci, comme les actions de joueurs en possession du ballon, les actions défensives, etc. (Roca et al., 2011). Des recherches ont démontré que les experts (joueurs de football professionnels) ont tendance à percevoir davantage d’éléments, tels que le joueur possédant la balle et les espaces (libres) autour de celui-ci que les non experts (Roca et al., 2011). Cependant, la façon dont les joueurs de football font le lien entre différents éléments, qui forme la base de la vision du jeu et de sa compréhension (i.e., les représentations) pendant un match ou un extrait de match, reste incomprise. Lors de notre étude empirique, un système de codage a été développé sur la base de la « théorie de l’habileté » (Skill Theory ; Fischer, 1980 ; Fischer & Bidell, 2006). Cette théorie suppose que les représentations ou impressions plus complexes sont fondées sur la liaison d’éléments simple (e.g., "le joueur envoie la balle à un autre joueur") en une structure plus complexe (e.g., "l'arrière gauche fait une passe au numéro 10", ce qui requiert une connaissance des positions des joueurs sur le terrain, des positions des coéquipiers ainsi que des types de passes). La complexité des représentations, telles que celles élaborées en continu lors du visionnage d'extrait de match, a été analysée de manière comparative parmi une population de joueurs professionnels et non professionnels (joueurs d'une ligue amateur) à l’aide du système de codage développé.

Les résultats ont montré que les joueurs possédant une plus grande expertise élaboraient des représentations d’un niveau de complexité supérieure. De plus, ces joueurs étaient capables de comprendre des actions de relativement plus grande complexité, au-delà du joueur possédant la balle (e.g., une relance ou une action défensive). En résumé, ce chapitre illustre la façon dont les facultés cognitives des joueurs peuvent être mesurées en termes de complexité ainsi que l’intégration des interactions des différents éléments par la formation (constante) de représentations.

Chapitre 3

Alors que le chapitre 2 s’est intéressé aux compétences cognitives à l’œuvre au cours de visionnages d'extraits vidéos, le chapitre 3 aborde la complexité de l’organisation du comportement moteur à la base de l’exécution d’un exercice sportif. Plus spécifiquement, ce chapitre est consacré à l’étude des variations des coups de rame au cours du temps lors d'une épreuve sur un ergomètre. Selon la littérature, la structure temporelle des fluctuations des mouvements fournit un aperçu de l'organisation dynamique sous-jacente (Van Orden et al., 2003). Si les mesures successives sont indépendantes des mesures précédentes, des variations aléatoires, appelées « bruit blanc », entre les mesures doivent être observables. Ce type de patron est censé apparaître au fil de mouvements contrôlés par un processus séquentiel, tels un programme moteur (Keele, 1986). Cependant, comme indiqué précédemment, nous avons commencé cette thèse avec le point de vue selon lequel la performance (dans ce cas les mouvements d'aviron) résulte de la complexité, ce qui signifie que les différents éléments impliqués dans la production motrice interagissent constamment entre eux, à différentes échelles temporelles. Un tel procédé peut être exprimé en un patron de variation plus structuré, appelé « bruit rose » (Kello et al., 2010 ; Van Orden et al., 2003). Lorsqu'une série de mesures montre du bruit rose, les mesures effectuées sur un grand intervalle de temps sont dépendantes à long terme (Diniz et al., 2011). Dans cette étude, par exemple, cela veut dire que le 400^{e} coup de rame n'est pas indépendant du 300^{e}, du 100^{e}, etc.

Afin de tester cette hypothèse, nous avons demandé à des rameurs de deux équipes d'aviron de réaliser 550 coups de rame à leur cadence préférée. Les variations des intervalles de temps entre les pics de force de mouvements ont été relevées afin d'effectuer une analyse comparative, puis une analyse non linéaire des séries temporelles enregistrées (Detrended Fluctuation Analysis ; Peng et al., 1993). Les résultats ont montré que pour chaque participant la structure temporelle de la variance s'écartait significativement du bruit blanc, et plus particulièrement, que les rameurs de la meilleure équipe développaient un patron de variation proche du bruit rose. Ces résultats supportent l'hypothèse selon laquelle une organisation motrice complexe est à la base de l'exécution des mouvements sportifs cycliques (i.e., aviron). Par ailleurs, comme les séries temporelles des rameurs de la meilleure équipe montrent davantage de bruit rose, la complexité de l'organisation motrice, telle que reflétée par le bruit rose, peut être un indicateur de l'expertise d'un rameur. Cependant, ceci devra être examiné plus profondément.

Chapitre 4

Dans le chapitre précèdent, nous avons examiné la complexité de situations hors contexte de compétition. Cependant, le contexte de compétition (à l'école, au travail, en sport), fournit aux acteurs des scénarios originaux d'évolution de leur progression (ou regression) à l'égard des buts qu'ils poursuivent, notamment au travers de l'évolution du score ou de la performance, des actions de l'adversaire, d'événements marquants comme les décisions arbitrales, du comportement du public, etc. Lorsqu'une personne ou une équipe voit son objectif de victoire s'approcher ou au contraire s'éloigner, cette même personne ou équipe peut entrer dans une spirale positive ou négative, appelée le momentum positif ou négatif (Briki, Den Hartigh, Hauw et al., 2012). Dans ce chapitre 4, nous cherchons à montrer cette dynamique du momentum psychologique au sein d'équipes de deux rameurs, telle qu'elle peut se manifester en termes de synchronisation motrice interpersonnelle, de performance, de cohésion perçue et de sentiment d'efficacité collective. Ce travail s'appuie sur une méthode d'investigation développée par Haken et al. (1985) – la méthode HKB – dans le but d'examiner expérimentalement la dynamique des processus complexes.

Dans cette étude, des équipes de deux rameurs sur ergomètre affrontaient un adversaire virtuel en compétition. Durant la course, les efforts – la force des coups de rame – et la coordination des mouvements des rameurs ont été mesurés continuellement. Afin de capturer la dynamique de variables psychologiques importantes pour une équipe, deux questions apparaissaient à l'écran toutes les minutes au cours de la course : une question sur la cohésion opératoire et une sur le sentiment d'efficacité collective. La cohésion opératoire représente le degré de coopération des membres d'une équipe pour atteindre un objectif commun (Carron & Hausenblas, 1998) ; l'efficacité collective représente le degré de confiance des membres de l'équipe dans leur capacité à exécuter avec succès la tâche collective. L'équipe a participé à deux courses avant lesquelles nous leur indiquions que le but était de battre l'adversaire en prenant une avance de 8 secondes sur celui-ci. Cependant, les scénarios de course étaient manipulés à l'insu des participants. Dans une des courses, les participants expérimentaient un scénario de momentum positif selon lequel l'équipe remontait progressivement d'une presque défaite (un retard de 6 secondes) jusqu'à être proche de l'objectif (une avance de 6 secondes). L'autre course faisait vivre à l'équipe une expérience de momentum négatif sous la forme d'un scénario symétriquement inverse du précédent.

Les variables cohésion opératoire et efficacité collective ont montré une tendance à la baisse pour la course à momentum négatif. Cette baisse était plus prononcée que la hausse observée lors de la course à momentum positif. Il semble donc que les équipes développent plus rapidement un momentum psychologique négatif qu'un momentum positif. De plus, les efforts de l'équipe diminuaient plus rapidement dans la course à momentum négatif et la coordination des rameurs était meilleure dans la course à momentum positif. Le fait que deux scénarios de course exactement symétriques soient associés à des patrons d'évolution des réponses non-symétriques suggère que le momentum psychologique est un phénomène dynamique qui montre des caractéristiques de dépendance temporelle typiques des systèmes dynamiques complexes. Nous avons montré que les états psychologiques des équipes ne sont pas seulement influencés par la position dans la course, mais aussi par le scénario selon lequel cette position a été acquise (i.e., avoir commencé par perdre ou gagner des secondes avant de remonter ou de se faire remonter).

Chapitre 5

Jusque-là, les recherches sur le momentum psychologique se sont principalement intéressées aux fluctuations psychologiques et (parfois) et aux variations des performances au cours d'une même compétition (cf. chapitre 4). Cependant, le momentum psychologique peut se développer à travers plusieurs compétitions, par exemple lors d'un tournoi ou sur une saison entière (Adler, 1981). Selon la théorie de la dynamique des systèmes complexes, les processus prenant place à court terme sont liés aux processus apparaissant à plus long terme (Newell et al., 2001). Basé sur le principe que le momentum psychologique est un phénomène complexe dynamique, ce chapitre avait pour but d'examiner la manière dont le momentum psychologique à long terme se développe à partir d'une série de matches distincts, ainsi que la manière dont le momentum psychologique intra-match est façonné par le momentum psychologique qui s'est développé sur le long terme.

Dans cette étude, nous avons demandé à des athlètes de participer à un tournoi d'aviron sur ergomètre se déroulant sur plusieurs courses. Nous avons informé les participants qu'ils pouvaient gagner de l'argent s'ils marquaient trois points sur le total des courses à réaliser, ces points dépendant du nombre de victoires. Pour chaque course, le vainqueur était le premier rameur à prendre une avance de 9 secondes sur son adversaire. Les scénarios de course étaient manipulés de sorte à répartir les participants sur deux groupes : un groupe gagnant les deux premières courses (groupe du momentum positif), le second perdant les deux premières courses (groupe du momentum négatif). Nous avons demandé aux participants de répondre à un item mesurant le momentum psychologique et un item mesurant le sentiment d'auto-efficacité, avant les deuxième et troisième courses. Les résultats ont montré que le groupe ayant gagné ses deux premières courses développait un momentum psychologique à long terme positif, alors que le groupe ayant perdu ses deux premières courses développait un momentum psychologique à long terme négatif.

Lors du troisième tour du tournoi, le cours de la course fut manipulé selon les principes de la méthode HKB (Haken et al., 1985). Dans cette course, tous les participants passaient progressivement d'une presque victoire (une avance de 6 secondes) à une défaite (un écart de 9 secondes). Dans le but d'examiner la dynamique du momentum psychologique durant cette dernière course, les participants ont répondu toutes les minutes de la course à des questions relatives à leurs perceptions de momentum psychologique à leur sentiment d'auto-efficacité. De plus, l'effort physique exercé par les rameurs a été continuellement mesuré. Les résultats ont montré que les perceptions de momentum et d'auto-efficacité diminuaient plus rapidement au sein du groupe ayant perdu les deux premières courses (le groupe ayant développé un momentum psychologique à long terme négatif) que pour le groupe ayant remporté les deux premières courses (le groupe ayant développé un momentum psychologique à long terme positif). En outre, les efforts des participants appartenant au groupe ayant développé un momentum psychologique à long terme positif pendant le tournoi étaient supérieurs.

Ces résultats fournissent une meilleure explication de la dépendance temporelle des réactions psychologiques que les précédentes recherches (Briki et al., 2013 ; Gernigon et al., 2010 ; chapitre 4) en démontrant que les processus à court terme (au fil d'une course) sont liés aux processus à long terme et vice et versa. Plus spécifiquement, un athlète développe moins aisément un momentum psychologique négatif s'il a développé un momentum psychologique positif à long terme (e.g., sur plusieurs compétitions).

Chapitre 6

Les chapitres précédents portaient sur l'analyse des processus dynamiques complexes sur une échelle temporelle relativement courte (pendant un match et sur plusieurs matchs). Ce type de processus peut généralement être analysé dans l'environnement spécifique dans lequel la performance a lieu. Cependant, pour des processus prenant plus de temps et s'étendant sur plusieurs environnements, cela devient malaisé. Prenons exemple sur le développement du talent ou le développement de la performance excellente. Les chercheurs et les philosophes s'interrogent sur les facteurs entraînant le développement de la performance depuis près de 150 ans. Bien que le débat sur l'identification de ces facteurs a toujours cours (Ericsson, 2013; Ericsson et al., 2013; Gagné, 2013), nous avons choisi une approche différente dans le chapitre 6. Sans nous intéresser davantage aux facteurs pronostiques spécifiques, nous avons, dans ce chapitre, examiné à partir de quel genre de modèle l'excellence se développe. Nous avons simulé différents modèles sur ordinateur, susceptibles de rendre compte des trajectoires de développement du talent individuel, mais aussi des différences interindividuelles associées à des distributions d'excellence spécifique à un domaine.

Nous avons supposé que l'excellence évolue au fil du temps, de débutant à un niveau final (excellent). Hormis cela, dans notre modèle, nous avons également émis l'hypothèse que plusieurs facteurs peuvent jouer, pouvant eux-mêmes varier avec le temps et s'influencer directement et indirectement. Par exemple, le don d'un enfant pour le tennis, le soutien de ses parents et de son entraîneur, etc. (Abbott et al., 2005; Baker et al., 2003; Phillips et al., 2010). Nous avons donc simulé des modèles sous forme des réseaux composés de 10 éléments, dans lesquels chaque élément est directement ou indirectement lié à d'autres composants (e.g., l'entraîneur influence les capacités de l'enfant, ce qui par la suite influence le soutien des parents, ce soutien à son tour influe positivement sur les capacités de l'enfant, etc.).

Le modèle de simulation a généré un certain nombre de patrons de trajectoires de développement du talent et de l'excellence conformes à la littérature sur le sujet (Simonton, 2001), tels que (a) un talent spécifique peut naître à des âges différents pour des individus différents, (b) les facteurs pouvant influencer le développement du talent peuvent changer avec le temps, (c) le processus de développement peut adopter plusieurs forme pour différents individus, (d) les indicateurs précoces annonciateurs de compétences excellentes futures sont souvent absents. De plus, les simulations de modèles ont généré des distributions asymétriques positives du rendement final de la performance, ce qui apparaît dans presque tous les domaines de performance (O'Boyle & Aguinis, 2012). Afin de clarifier ce dernier point, l'exemple suivant illustre une distribution asymétrique positive du rendement de la performance en sport. Seul 404 joueurs ont gagné un tournoi ATP. Parmi ceux-ci, 74 d'entre eux n'en ont gagné qu'un et uniquement trois joueurs exceptionnels ont gagnés plus de 80 tournois : Federer, Lendl et Connors (www.atpworldtour.com, consulté le 5 novembre 2014).

D'après les résultats des simulations, il est probable que le développement du talent puisse être considéré comme un processus complexe et dynamique. En d'autres termes, l'excellence se développe probablement à partir des structures de réseaux dynamiques.

9.2 Conclusion

Cette thèse s'est attachée a montrer comment les processus liés à la performance, impliquant plusieurs composants interagissent et évoluent avec le temps et peuvent être étudiés et compris en appliquant une approche de la complexité. Nous avons utilisé la « théorie de l'habileté » (chapitre 2), les techniques de séries temporelles non-linéaires (chapitre 3), la méthode HKB (chapitres 4 et 5) et la simulation informatique (chapitre 6). Les résultats des différentes études ont montré que (a) les joueurs de football les plus experts forment des représentations plus complexes lorsqu'ils visionnent des extraits de matches, (b) il semble qu'une organisation motrice complexe est sous-jacente à l'exécution des coups de rame en particulier pour les meilleurs rameurs, (c) le momentum psychologique est caractérisé par des changements dans les facteurs psychologiques et la performance qui sont dépendants du temps, c'est-à-dire de leur propre histoire, et (d) les excellentes performances se développent probablement par l'interaction continue entre composants personnels et environnementaux directement et indirectement liés.

Les résultats de cette thèse montrent qu'une approche de la complexité fournit des techniques précieuses pour acquérir de nouvelles connaissances sur le quand, le pourquoi et le comment certains états psychologique changent. Les études effectuées étaient pour la plupart de nature fondamentale, mais peuvent offrir des suggestions concrètes pour les recherches futures et les applications pratiques. Ainsi, il semble particulièrement pertinent de mettre l'accent sur l'interaction entre les composants au cours de temps, ou sur la structure du réseau dans lequel les composants sont actifs. Cela signifie qu'il est important de considérer la manière dont nous pouvons intervenir d'une façon positive sur les interactions ou les propriétés des structures. Dans le chapitre 3, par exemple, nous avons proposé qu'une organisation dynamique plus complexe soit impliquée dans les coups de rames des meilleurs rameurs, comparativement à ceux de rameurs de niveau moins élevé. Ainsi, les meilleurs rameurs sont stables dans leurs mouvements, mais suffisamment souples pour s'adapter. La possibilité d'entraîner cette « stabilité souple » pourrait être étudiée, par exemple, en pratiquant des coups d'aviron selon un patron de fréquence à bruit rose en utilisant un métronome (Marmelat et al., 2014). Une telle stratégie pourrait être comparée à une stratégie plus classique basée sur la fixité et la rigidité des rythmes.

Dans le cas du momentum psychologique, il devrait être possible d'identifier les stratégies les plus à même de faire converger moins rapidement les variables psychologiques et la performance vers un patron de momentum psychologique négatif (Briki, Den Hartigh, Hauw et al., 2012). La manière de demander des temps mort dans un match pourrait relever de telles stratégies testées empiriquement (cf. Briki, Doron et al., 2014). Les temps morts seraient alors considérés comme des temps de relaxation (Haken et al., 1985) nécessaires au système pour se restabiliser après avoir été déstabilisé par un scénario événementiel de momentum négatif.

En ce qui concerne le développement des talents, il semble important d'introduire ou de renforcer des liens positifs au sein du réseau, favorisant ainsi le développement tout en protégeant des éventuels échecs. L'importance d'établir une structure optimale du réseau est par exemple illustrée par les travaux de Van

Yperen. Alors que la plupart des études ont misé sur l'importance du talent naturel et de la formation, Van Yperen a montré que le soutien des parents et certains éléments psychologiques, comme l'engagement envers un objectif, jouent un rôle important dans le développement d'un athlète (Van Yperen, 1995a; 1998; 2009). En termes de réseau, il semble important que les compétences d'un athlète se développent dans un réseau riche, dans lequel la probabilité de développer des liens positifs entre les différents éléments est maximisée (pour un exemple pratique intéressant, voir Van Yperen, 1995b). De ce fait, comparativement à des programmes où les enfants vivent en pensionnat, sont traités durement et dans lesquels l'accent est mis sur un seul élément (e.g., entraînement intense), il est probable que les réseaux riches entraînent une évolution positive pendant et après la carrière sportive, mais aussi dans des carrières relatives à d'autres domaines de performance (e.g. professionnelle).

En résumé, cette thèse a démontré plusieurs applications d'une approche de la complexité. Sur la base de cette approche, nous sommes arrivés à des nouvelles connaissances sur la complexité et la dynamique des processus de performance, à la fois lors de l'exécution des tâches (sportives) ainsi que sur du long terme au cours duquel le talent se développe. Le prochain défi sera de spécifier et de traduire les processus complexes et dynamiques sous-jacent aux processus psychologiques et de performance dans des applications concrètes pour la pratique.

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Acknowledgements

One key characteristic of complexity is that a given state cannot be reduced to the contributions of specific identifiable factors, but rather emerges from the interactions between those factors. Today, while I'm reflecting on the past years, I think that my thesis, and the process of writing it, was indeed a complex process. It is therefore difficult to exactly specify who contributed to what extent, and how much each supervisor added to which parts of my development. However, I would like to mention some key factors that shaped the process, which ended in this thesis.

To start, I am very grateful to my supervisors Paul, Christophe, Nico, and Ralf. Without the commitment and confidence of Paul, Nico, and Christophe at the start, I would not have had the opportunity to apply for a PhD grant in the first place. Christophe, a year before we met, I read a paper of you about the potential of the dynamical perspective in sports, and I was certain this was a topic I wanted to learn more about. Thank you for hosting me during my master's internship before my PhD, and for further triggering my enthusiasm about dynamical systems in sports. During my PhD project you have contributed greatly to my academic skills, including writing papers, proposals, and setting up experimental studies. I hope we will continue collaborating in the future.

Nico, door jou waren een aantal cruciale netwerkcomponenten aanwezig om een productief promotietraject mogelijk te maken. Heel erg bedankt voor het bieden van de mogelijkheid om in Groningen te komen werken aan een onderzoeksvoorstel vier jaar geleden en voor je efficiente en gestructureerde manier van werken. Ik heb veel gehad aan je snelle en scherpe feedback op de experimentele designs die we op hebben gezet en de artikelen die we hebben geschreven. Daarnaast was het altijd heerlijk om samen te praten over onze gedeelde passie: sport. Ik ben blij dat we blijven samenwerken, onder andere in de master Talent & Creativity! Paul, je bent briljant en ik ben blij dat, zoals Erdös het zou omschrijven, je geest altijd open was. Als we een afspraak hadden, voelde dit als een kans om zoveel mogelijk kennis uit je te trekken, waar ik dan de rest van de week lekker mee aan de slag kon om nieuwe theoretische en onderzoeksideeën uit te werken. Je bent een fantastische mentor, niet alleen in academische zin, maar ook op persoonlijk vlak. Bedankt voor alle mogelijkheden

die je me hebt geboden tijdens mijn promotietraject, onder andere door analysemethoden en theoretische perspectieven met me te delen, maar bijvoorbeeld ook door een bezoek aan Florida Atlantic University te organiseren. Ik ben ook blij dat je me in contact hebt gebracht met Ralf drie jaar geleden. Ralf, je was een erg waardevolle en inspirerende co-promotor. Door jou is ons onderzoeksproject verrijkt met een intrigerend aspect van complexe dynamische systemen: Fractaaldynamiek. We hebben veel discussies gevoerd over complexiteit en mogelijke nieuwe studies en ik hoop dat we die discussies nog vaak zullen voeren de komende jaren.

I would also like to thank the reading committee of my thesis: Robin Vallacher, Benoît Bardy, and Koen Lemmink. Robin Vallacher, thank you very much for hosting us in Boca Raton, for our discussions about dynamical social psychology, sports, and the Action Identification Theory, and for introducing us to other great researchers at your university. I am very grateful to have had such an inspiring and stimulating experience during my PhD studies.

Eén van de belangrijkste personen die me in de eerste plaats heeft geholpen om me verder te verdiepen in de sportpsychologie en om meer te leren over dynamische systemen via een stage in Montpellier, is de opa van de sportpsychologie in Nederland: Frank Bakker. U was niet direct betrokken bij mijn promotietraject, maar mede dankzij uw hulp en begeleiding gedurende de (pre)master aan de VU heb ik de eerste basis kunnen leggen voor een wetenschappelijke carriere en een samenwerking met Montpellier. Ik zie ernaar uit om u te treffen bij de verdediging.

In the sunny south of France, thanks a lot to the colleagues and institutions who supported my project. Special thanks to the école doctorale 463 Sciences du Mouvement Humain with its director Reinoud Bootsma; laboratory Epsylon, which provided my working facilities in Montpellier; and Laboratory Movement to Health (M2H) for the collaboration. Of M2H I'd like to thank Ludovic Marin, Robin Salesse, and Vivien Marmelat in particular for their useful help and suggestions in the project on ergometer team-rowing (Chapter 4).

Aan de RuG wil ik mijn gezellige kamergenootjes Monica, Megan en Jana bedanken en alle andere collega's, met name van de afdelingen organisatiepsychologie, ontwikkelingspsychologie en de onderwijseenheid. Ik voelde me op alle drie de afdelingen thuis en had een optimale mix van gezelligheid en leerzame onderzoeksbesprekingen. Daarnaast heeft de diversiteit aan contacten geleid tot een aantal leuke, interessante en ook zeer verschillende onderzoekssamenwerkingen met onder andere Lise, Namkje, Melvyn, Naomi, maar ook met Harjo bij Bewegingswetenschappen. Dankjulliewel daarvoor! Verder wil ik José heel erg bedanken dat je bij mijn onderwijsinzet altijd rekening hebt gehouden met mijn “speciale” situatie (regelmatig in Montpellier) en het onderwijs zo goed op mijn programma hebt laten aansluiten. Mede hierdoor kon ik in relatief korte tijd mijn proefschrift afronden. Daarnaast, Naomi en Steffie (geen zorgen Steffie, je komt later nog een keer terug in het verhaal), de meeste gezellige bezoeken aan congressen en universiteiten waren toch wel met (één van) jullie, met als hoogtepunt onze periode in Florida met Paul! Tot slot Xavi, we had great times watching soccer, having drinks, talking about sport psychology, and collaborating during your period in Groningen and after that. You are a great friend and colleague.

De ondersteuning de afgelopen jaren kwam niet alleen vanuit mijn (voormalige en huidige) begeleiders en collega’s, maar ook mijn studenten. Een paar studenten wil ik in het bijzonder noemen, omdat zij van grote waarde waren tijdens het opzetten en de uitvoering van de (pilot) studies in de hoofdstukken 2 tot en met 5. Dankjewel Jaap, Jelmer, Jeremy, Marjon, Mart, Ozan en Sten (omdat jullie allemaal even belangrijk waren, heb ik jullie namen in alfabetische volgorde gezet). Kees, jij ook bedankt voor de fijne samenwerking tijdens onze tennisstudie! Daarnaast wil ik de instrumentatiedienst, met name Pieter, Remco en Mark, bedanken voor jullie tijd en inzet bij het installeren van de onderzoeksopzet met de roei ergometers. Jullie hulp was van onmisbare waarde voor de uitvoering van de studies in de hoofdstukken 3, 4 en 5.

De bovengenoemde personen waren vooral op een directe manier betrokken bij mijn onderzoeksprojecten. Maar als u niet bent begonnen met het lezen van het dankwoord, maar hier pas bent aangekomen na het uitvoerig doornemen van het proefschrift, weet u nu ook dat componenten die indirect aan het proefschrift gerelateerd zijn, zoals sociale factoren, ook een belangrijke rol spelen. Allereerst wil ik de mannen van de Roger Federer whatsapp groep bedanken, in het bijzonder Machielsen, Jens, Thoden en Cupido. Helaas zijn jullie uit Groningen vertrokken, maar als we elkaar weer troffen in Groningen of het westen, volgden er toch altijd weer heerlijke avondjes, ik hoop jullie nog heel lang als vriend te

houden. Jens en Thoden, ook bedankt nog voor het helpen filmen van de tafeltenniswedstrijden een paar jaar terug en sorry dat het artikel steeds afgewezen werd. Jullie zijn fantastisch en verdienen zeker een plek in een officiële acknowledgements-sectie, dus bij dezen. En natuurlijk de persoon waar stelling 10 wat minder op slaat en die in ieder kledingstuk en met ieder materiaal goed tennist, Andries Cupido. We hebben heel veel dingen samen gedaan de afgelopen jaren in stressvolle, vermoeiende, gezellige en memorabele situaties (in het bestuur, tennis en nog meer daarbuiten) en ik ben blij dat je erbij bent als mijn paranimf!

Al zijn de bovenstaande vrienden al een tijdje weg uit het noorden, er kwamen nieuwe gezellige feestjes en avonden in de Minnaar voor in de plaats met Marieke, Mads, Charmaine, George, Joki, Annika, Elisa en Diederik. Bedankt! Als ik de Minnaar noem, mag ik ook Gert niet vergeten, de avondjes met jou zijn altijd uiterst amusant. Hopelijk keer je snel weer terug naar Groningen.

Als ik na een periode werken in Groningen weer in Montpellier aankwam, hoefde ik de Nederlandse gezelligheid niet te missen. Bedankt Joris voor het kamertje in je appartement gedurende de eerste maanden in Montpellier. Marco, je hield me iets teveel van mijn werk in ons kantoor, maar het was een mooie periode toen jij in Montpellier was! Tot slot, Liesjet, jij maakte het leven in Montpellier allemaal een stuk leuker en gemakkelijker. Je stond altijd klaar als ik weer eens in de knoop zat met de Franse administratieve rompslomp. Maar ik ga vooral onze fijne bier-en-pizza avonden missen en de borrels in Analog, de prachtige bar van Kevin en Karen.

Dan, the accidental perfection of nature, het resultaat van een complex proces dat op de kaft is weergegeven. De zandsculptuur is na de foto's afgebroken, maar onze vriendschap is altijd blijven staan. Sanne, dankjewel dat je er altijd bent geweest en nu ook weer voor me klaarstaat.

Als we het dan toch over de natuur hebben, van een tennisvriend (Anne) heb ik geleerd dat je na elk gewonnen tennistoernooi, in elke speech of dankwoord, je ouders moet bedanken zonder wie je überhaupt niet in staat was geweest om prestaties te leveren. En dat is ook zo in meerdere opzichten. Mijn ouders hebben in alle periodes dat ik mijn dromen nastreefde (met name in tennis en de wetenschap) achter me gestaan, dankjulliewel daarvoor! En natuurlijk mijn broertje Hans, trots als ik was toen je ruim 24 jaar geleden geboren werd, ben ik dat nu nog steeds. We zijn in zo’n beetje alles verschillend, maar tegelijkertijd ook beste vrienden.

En dan wil ik nu graag eindigen met het beste hoofdstuk van mijn PhD: Steffie. Het begon ruim vier jaar geleden, in dezelfde periode dat ik aan mijn onderzoeksvoorstel ging werken. Jij bent met me meegegaan naar Montpellier om me te helpen een beurs binnen te halen voor dit onderzoek. Dat is gelukt en vervolgens heb ik een paar prachtige PhD-jaren gehad met jou als vriendin en leukste collega. Jij bent het hoofdstuk waar ik het meest trots op ben en waar de mooiste plaatjes in zitten.

Curriculum Vitae

Ruud den Hartigh was born in Nieuw-Beijerland, on August 16th, 1984. After finishing his secondary education, he worked on a full-time tennis career for two years. After this period, Ruud moved to Groningen, where he started his studies in Psychology in 2004, and was involved in various student committees and boards. After his bachelor's program at the University of Groningen, Ruud moved to Amsterdam in 2008 for the pre-master's and a master's program in Human Movement Sciences (Sport, Exercise, and Health) at the VU University, which he combined with the program 'European Masters in Exercise and Sport Psychology'. During this period, he did a research internship at Montpellier 1 University, where he wrote his two master's theses on the dynamics of psychological momentum in sports. After a successful application for a PhD position in Montpellier in 2011, based on a collaboration between the Universities of Groningen and Montpellier, Ruud wrote his dissertation in alternate periods at these two universities. In March 2015, Ruud started a position as Assistant Professor Talent and Creativity at the University of Groningen.

Publications

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